Three Essays on Residential Mortgage Defaults, Loan Modifications and Post-Default Outcomes.

Doctor of Philosophy (PhD)

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Declaration of Original Authorship

I confirm that this is my own work and the use of all material from other sources has been properly and fully acknowledged.

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Abstract

Residential mortgages represent a crucial segment within the financial and lending industry across major economies. Their significance stems primarily from the market's size, a result of the combination of substantial loan amounts and widespread presence in the consumer credit sector. Consequently, residential mortgages constitute a significant proportion of the assets managed by financial institutions. In addition, this type of loans is central to numerous policy and governmental initiatives, reflecting the importance of the underlying collateral for a substantial number of citizens in most developed countries. Lastly, given their pivotal role, residential mortgages have been at the heart of various crises over the years and continue to be closely monitored due to their critical importance in contributing to overall financial stability.

A substantial corpus of academic literature emerged following the Global Financial Crisis, exploring various dimensions of mortgage financing, including its relationship with the broader economy, and the events and market disruptions that caused the collapse of this sector. Nevertheless, as the crisis gradually receded, certain pivotal questions and research areas have seen diminished interest, overshadowed by other subjects. This Thesis aims to enrich the existing body of literature by offering new insights into two significant aspects of residential mortgages that remain pertinent today, despite receiving scant attention in recent years. The first research domain focuses on correlation; the second investigates mortgage dynamics in response to specific lifecycle events, such as modification and default.

Correlation plays a crucial role in determining both regulatory and economic capital, as it quantifies the interconnectedness of loans within the same asset class. Hence, the precision of the correlation parameter is vital for accurate risk assessment and manage-

ment. Within the regulatory framework, the Basel Committee on Banking Supervision (BCBS) has set the correlation for residential mortgages at a fixed value of 15%. Although this value is deemed to be sufficiently conservative, there is limited evidence supporting its flat nature. This research primarily seeks to ascertain the validity of this assumption by investigating the presence of significant variations in default correlation across different segments of the residential mortgage market. Moreover, the study examines the impact of correlation on lenders' loan pricing strategies and questions whether current regulation implicitly encourages regulatory capital arbitrage.

Throughout the lifetime of a mortgage, various events can alter the standard repayment trajectory, which in turn has significant implications for lenders, borrowers, and stakeholders. The second and third empirical chapters of this Thesis analyse the determinants that characterise mortgage resolutions following loan modification and default, respectively. Specifically, this Thesis enhances existing research by examining how policy changes and mortgage market breaks have impacted consumers behaviour after the occurrence of these events. In particular, the second empirical study analyses the outcomes of post-modification and its determinants following the cessation of the Home Affordable Modification Program (HAMP), implemented by the US government to address the escalating defaults triggered by the Global Financial Crisis. Conversely, the third empirical chapter examines post-default resolutions and their determinants across three periods: before, during, and after the crisis.

This study utilises mortgages originated in the United States by the Federal Home Loan Mortgage Corporation (Freddie Mac). The data under examination encompasses over 20 years and offers a nationwide scope, thereby providing a novel viewpoint within the existing literature, which has predominantly focused on either sub-prime portfolios or state-specific mortgages.

Acknowledgments

I dedicate this Thesis to my grandmother Edelvaise. A living example of endurance against adversity, an embodiment of love for life and the beauty of its small things, and of blissful faith.

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Chapter 1

Introduction

1.1 Background, Motivation and Scope of the Study

Residential mortgages have a central role in many economies, particularly in Europe and America, underpinning the significance of empirical and theoretical studies related to this financial product. The relevance of residential mortgages touches several different aspects within the financial industry. Primarily, residential mortgages constitute a substantial part of the financial sector in numerous countries. For instance, in the United States, this segment represents the largest consumer debt market, comprising 70% of total consumer debt (Federal Reserve Bank of New York (2024)). This is further corroborated by data from other jurisdictions like the UK, where nearly 88% of total lending to individuals is secured by dwellings (Bank of England (2022)). As such, the integral role of residential mortgages in household financial decisions is soon underscored, often being the most substantial commitment in a borrower's lifetime. These two critical aspects (i.e. coverage and pivotal role for consumers) yield significant and interconnected implications. Firstly, due to the crucial role in both local and global economies, mortgages have frequently been at the heart of economic crises, such as the US Savings and Loans Crisis in 1980, the UK Housing crisis in 1990, and the Global Financial Crisis in 2007-2008. Enhancing the understanding of this market and the triggers for its periodic crashes can aid in preventing or mitigating similar events, a goal that current international regulations and standards strive to achieve (Bank for International Settlements (BIS) (2013)). Secondly, due to its significant impact on consumer expenditure, policymakers and governments intervene substantially with programs and schemes affecting interest rates, lending standards, and social welfare, which consequently influence housing and lending sectors. Thus, a deeper understanding of this market, its cycles, and its risks is crucial for both academia and industry.

Residential mortgages are secured loans that facilitate the purchase of residential properties, whether for personal habitation or investment purposes. Although they are relatively simple financial instruments compared to more sophisticated tools, their evolution following origination unfolds in several stages and can lead to non-standard outcomes. Mortgages are originated by credit institutions through an application process, where quantitative and/or qualitative criteria are employed to assess whether the new loan meets the originator's risk appetite[1]. These criteria are based on a combination of borrower, loan and property characteristics, and can be evaluated through quantitative tools (e.g. scorecards) or expert judgement. Once the mortgage is approved, the borrower begins repaying the loan, with monthly instalments generally varying depending on the amount requested, amortisation type (i.e. interest-only or annuity), loan term, interest premium and interest type (i.e. fixed or adjustable rate). A standard mortgagor pathway would involve regular repayment of monthly instalments until maturity, although this scenario is not always what banks effectively encounter. Two main competing outcomes constitute a deviation from the standard pathway: prepayment and default. The first outcome is generally favourable for the borrower, as it allows for early loan settlement either due to a full repayment given other funds, or because the borrower is refinancing the loan elsewhere at better conditions. However, although the lender recovers the outstanding balance in full, it loses future interest payments. On the other hand, default represents a negative outcome for both lenders and mortgagors. When a borrower fails to meet their repayment obligations, the loan enters into arrears and, upon reaching a certain threshold—typically three months of missed payments—it is deemed to be in default. From this juncture,

[1]The risk appetite refers to the degree of risk-taking that a financial institution internally establishes. This implies that loans with a certain degree of risk might not meet such requirements and are therefore rejected. A loan that would be suitable for one bank, based on its financial plans, might not be equally suitable for another credit institution.

there are three possible outcomes: the borrower might self-cure[2], the lender may assist the borrower in resuming regular payments, or, if these options are not viable or successful, the lender may seek to recover as much as possible through other means. The second outcome often involves renegotiating the loan to reduce the monthly payments. The third outcome, on the other hand, entails the liquidation of the mortgage; the lender repossesses and sells the property securing the loan to recover the outstanding balance. Both loan modification and liquidation are undesirable for the credit institution, as they result in the loss of either interest or principal, with the latter being more detrimental. It is evident that these outcomes may overlap during the lifespan of a mortgage. For instance, a loan might be modified and subsequently prepay, default, or be liquidated. However, it should be noted that liquidation and prepayment are terminal statuses. These various potential pathways underscore the complexity of the mortgage lifecycle, highlighting the numerous risks credit institutions face when managing this type of asset.

From a risk-management standpoint, research on residential mortgages began to gain prominence towards the end of the 1990s. Seminal works by Quercia and Stegman (1992), Schwartz and Torous (1993), and Capozza et al. (1997) explored the factors influencing default, while studies by Clauretie and Herzog (1990), Lekkas et al. (1993), Calem and LaCour-Little (2004), and Qi and Yang (2009) provided a detailed analysis of loss-given-default. These two aspects — default and loss-given-default — are critical to mortgage risk management as they assist in predicting potential losses. Despite these early studies and existing risk-management frameworks, it was not possible to either adequately prevent nor mitigate the devastating impacts that Global Financial Crisis (GFC) had on the financial markets. As a result of the economic downturn, largely stemming from the mortgage market, related literature significantly amplified due to the absence of sufficient foresight and its unparalleled impact on financial stability.

[2]It is important to note that missed payments adversely affect a mortgagor's credit history, thereby making future borrowing more challenging. Consequently, borrowers are motivated to self-cure to minimise damage to their credit scores.

The gradual recovery from the crisis led to a pause in literature production on the subject of mortgage behaviour. Many topics, initially analysed in the midst of the Global Financial Crisis (GFC), have remained crystallised to the context of financial hardship. However, despite initial stagnation, the mortgage market continued to expand and borrowers likewise continued to exhibit default patterns. For instance, the US residential mortgage market approached \$16 trillion in the third quarter of 2023[3] (Banking Strategist (2022)). Concurrently, mortgage dynamics evolved, exhibiting markedly different behaviour due to regulatory changes and economic transformation. Indeed, many previous assumptions and findings may no longer be valid in the current economic context, which significantly deviates from the crisis period. This research aims to address some of these gaps and provide a more contemporary perspective on the research areas pertaining to the mortgage market under examination.

This Thesis investigates two significant yet little explored areas in recent mortgage-related literature. The first area examines mortgage market's response to economic shocks through the lenses of correlation. The second area, split into two distinct studies, aims to understand the behavioural changes of mortgagors and lenders over time, specifically focusing on post-modification and post-default resolutions.

The first line of research investigates the correlation of mortgages inferred from defaults. The correlation parameter measures the interconnectedness of assets under economic downturns, serving as a crucial factor from both regulatory and portfolio management perspectives. International regulation mandates a constant value of 15% for capital requirements (BCBS (2021)), and this identical assumption, frequently country-adjusted, is commonly employed by risk managers for internal capital estimation. Nevertheless, such a fixed value may fail to encapsulate the intricate and diverse reactions of mortgage portfolios to financial turmoil. Building upon Cowan and Cowan (2004) work, the first study enhances the understanding of this vital parameter by utilising the Global Financial Crisis as a suitable analytical laboratory. Employing a unique method to deduce correlation from mortgage defaults, the study

[3] The overall residential mortgage market size is divided into Single-Family (\$13.864 trillion) and Multi-Family (\$2.164 trillion).

enriches existing literature by investigating the heterogeneity of mortgage correlation and its susceptibility to borrower- and loan-level characteristics overlooked by Cowan and Cowan (2004). Furthermore, the study examines the relationship between correlation and mortgage pricing, exploring how the constant value established by international standards influences lenders' decisions.

The second line of research investigates behavioural changes in mortgagors and lenders following the implementation of government programs and alterations to the mortgage market. Initially, I examine the determinants and outcomes after modification. The literature on mortgage modification has grown substantially due to the increase in defaults triggered by the subprime crisis, aiming to comprehend the efficiency of renegotiations, the influencing factors on its provision, and the connection between financial institutions and servicers. This field of study has been profoundly shaped by the introduction of US government programs such as the Home Affordable Modification Program (HAMP). However, despite extensive exploration of this topic, even the most recent studies (Schmeiser and Gross (2016) and Voicu et al. (2011)) exhibit limitations in geographical coverage and portfolio representativeness. Moreover, the most pertinent papers are temporally constrained, as they assess post-modification outcomes only up to the point when the program was still active. Hence, I enhance this second research strand by investigating how post-renegotiation outcomes evolved after public schemes were phased out, and were fully incorporated into the mortgage sector. This assists in determining which modification measures prove effective in the long term and how consumers respond to contractual term changes in more recent periods.

The concluding study centres on a complementary aspect of the second research stream that explores the dynamics between lenders and borrowers throughout mortgage market cycles. Specifically, it scrutinises how borrowers respond following the reach of default status (i.e., post-default outcomes), and evaluates the evolution of its determinants over time. The mortgage market cycle is segmented into three key phases: pre-, during-, and post-Global Financial Crisis (GFC) periods. Similar to the second paper, this study enables a comprehensive examination of US mortgage market dynamics from 1999 through 2022, thus spanning over two decades. However, unlikely to it, it clearly separates even the pre-crisis period from the rest. By expanding existing literature that previously investigated post-default outcomes (Been et al. (2013), Chan et al. (2014) and Voicu et al. (2012)), this study uniquely takes into account economic and policy shifts to comprehend the evolution of post-default outcome determinants. This is crucial, as all preceding literature explored this phenomenon either prior to the GFC or at its peak, which instead solely mirrors a distressed behaviour that is no longer applicable in the contemporary economic climate.

My interest in mortgages primarily originates from my professional experience. I commenced my job at Moody's Analytics in 2015, as part of the consumer credit analytics team. Here, I had the opportunity to model Probability of Default (PD), Prepayment and Loss Given Default (LGD) for retail portfolios, particularly focusing on the asset class at the centre of this Thesis. The exposure to mortgage credit risk modelling unveiled the myriad facets and research perspectives that retail loans can offer, further supplemented by consulting projects for clients. The close interaction with the mortgage universe revealed the numerous insights this asset class can provide, along with its complex nature and the associated challenges arising either from modelling or from data constraints. Such experience enhanced my understanding of clients' needs and the urgency to accurately manage and monitor their portfolios, in response to regulatory pressures or internal reporting requirements. Naturally, this necessitates a comprehensive understanding of the mortgage market itself, which also influences my work expertise in econometric modelling. The in-depth exploration facilitated by this study has made me aware of many intricate aspects of mortgage mechanics, which in turn influences its modelling. This has encouraged me to pose incisive questions and to extend my knowledge beyond existing boundaries. Consequently, working on this Thesis has primarily been instrumental for my personal knowledge enhancement and professional growth.

Secondly, the insights gathered here hold practical implications and can significantly influence both modelling and thought leadership within the sector. This was realised in a twofold way. First, as I presented the study on mortgage correlation to a group of practitioners, I received a large number of questions regarding its applicability to other segments and varying jurisdictions. This demonstrates risk-managers' willingness to enhance existing frameworks, not merely depending on regulatory directives, and to more accurately capture the inherent risk of consumer portfolios from a correlation perspective. Thus, by providing a replicable methodology that can augment portfolio risk management and internal capital calculations, this Thesis expands the perspective on this topic. Conversely, the practical implications of the second and third studies are derived from my daily work experiences. In my role of credit risk modeller, I have engaged with numerous econometric models related to the prediction of default, prepayment, and loss given default. However, these models seldom account for the underlying complexity of mortgage dynamics. For instance, they hardly differentiate between the behaviour of modified and non-modified mortgages or, in post-default analysis, typically utilise a single number calculated over the entire sample period to depict cure (or exit from default). Although I acknowledge that time and data constraints often impede the development of more sophisticated frameworks, the second and third studies helped to highlight the principal factors contributing to less investigated mortgage dynamics, as well as the alterations caused by market disruptions that could potentially improve or disrupt existing structures.

1.2 Main Research Contributions

This Thesis aims to contribute to mortgage market research. The analyses undertaken and related findings are oriented towards portfolio risk-management and credit risk modelling. The Thesis encompasses two primary areas. The first pertains to mortgage correlation, while the second explores mortgage market and policy breaks to inform post-modification and post-default outcomes respectively. Each stream is treated separately in this section, which summarises the main contributions.

Correlation serves as a crucial parameter for both corporate and retail portfolios. Within a corporate context, correlation can be readily measured, given the known, marketable asset value. Extensive literature investigates correlation for corporate asset classes, examining how it varies with firm size (Lopez (2004)) or its susceptibility to breaks (Adams et al. (2017)). Regrettably, this is not directly applicable to retail portfolios, including mortgages, because the asset is not marketed and its value is consequently unknown. Therefore, the only viable alternative is to deduce correlation from default or loss data. To date, within the mortgage context, only Cowan and Cowan (2004) has investigated the topic of interest of this first analysis, i.e. whether correlation is a static value or varies depending on loan characteristics. However, Cowan's analysis is limited to subprime lending and, most importantly, it encompasses a period which precedes the Global Financial Crisis. Post-crisis, other researchers, such as Neumann (2018), Geidosch (2014) and Botha and van Vuuren (2010), have explored mortgage correlation using loss or charge-off data. Nonetheless, none of these authors have scrutinised whether Cowan and Cowan (2004) findings remain valid post the Global Financial Crisis. Furthermore, the adoption of a uniform value for mortgage correlation by BCBS (2021), originating from Calem and Follain (2003), did not determine further investigations into this pivotal parameter. Notably, these values were derived before the Global Financial Crisis. Given this background, the first empirical study aims to address the following questions:

- To what extent is the assumption of a uniform value realistic in representing mortgage correlation? If it is not, what specific mortgage characteristics influence the heterogeneous nature of this parameter? Does the value established by regulators serve as an accurate and adequately conservative benchmark for capturing mortgage correlation?

- How do banks and financial institutions incorporate correlation in the process of mortgage pricing? Is there a connection between correlation and the pricing of mortgages? Does the uniform value set by regulatory bodies encourage riskier lending due to the protection guaranteed by regulatory compliance?

The first paper contributes to both these questions as follows. Firstly, I corroborate the supposition of Cowan and Cowan (2004) that the responsiveness of mortgages to market downturns is governed by specific attributes. While the direction and significance of common variables such as Credit Score and Loan to Value are maintained, I further reveal that the most powerful influencing factors on correlation variability have been overlooked in Cowan and Cowan (2004) research. The findings suggest that factors such as loan balance and debt-to-income ratio drive a more pronounced response during a downturn and contribute to a higher variability in mortgage correlation. Furthermore, I establish that the 15% threshold set by regulators is adequately conservative, even in the context of the Global Financial Crisis.

The second contribution concerns mortgage pricing and regulatory standards. I examine the correlation between mortgage pricing, with a focus on the mortgage premium, and, after controlling for standard determinants of mortgage pricing (e.g., Credit Score, Loan to Value, Number of borrowers), I reveal that the non-flat correlation parameter is not consistently priced across lending institutions. As a second contribution, the result indicates that only the Global Systemically Important Banks, which are subject to international regulatory standards, price correlation negatively. This could imply that current regulation, by enforcing a flat conservative value, may inadvertently encourage lending into correlated (and potentially more profitable) portfolios since lending institutions are protected by regulatory compliance.

In the second empirical chapter, the focus is on the analysis of post-modification outcomes and their determining factors. The Global Financial Crisis led to a rise in mortgage renegotiations, which were not initially a preferred resolution due to their lower profitability compared to foreclosure. However, the increase in defaults and financial hardship necessitated a change in approach towards struggling borrowers. This led not only to individual lenders taking initiative, but also to the US government's introduction of the Home Affordable Modification Program (HAMP), designed to promote beneficial modifications for borrowers, lenders, and investors. This significant intervention, coupled with a consequent rise in modification volumes, prompted a more thorough analysis of mortgage renegotiations from various perspectives. Among the many aspects of modifications, the second study primarily investigates post-modification outcomes. Pioneering analyses in this area were conducted by Quercia and Ding (2009), Haughwout et al. (2009) and Goodman et al. (2011), prior to the introduction of

HAMP, while notable contributions post-HAMP were made by Schmeiser and Gross (2016) and Voicu et al. (2011). These studies affirm the positive impact of payment reduction in maintaining the borrower's current status, as well as the successful effect of government intervention. However, due to limitations in data and analysis, there remain gaps that this research seeks to address:

- Which post-modification outcomes can be observed following the phasing out of the HAMP program? Did HAMP modifications maintain their effectiveness over a prolonged period? To what extent did the same types of modifications prove effective outside of government intervention?
- Is a modification necessary for all borrowers to keep up with payments, or is this option often strategically chosen? What additional insights can the Covid-19 period provide in this regard?
- To what extent are modifications effective even for prime portfolios?

Utilising a substantial sample of US mortgages, this study makes several contributions to the research questions just made. Firstly, it is demonstrated that payment relief is an effective strategy to ensure borrowers remain current, persisting even after the cessation of HAMP and within prime portfolios only peripherally addressed in existing literature. However, this study also establishes that the impact of different modification measures fluctuates over time, underscoring the fact that certain types of modification are more effective than others in periods of financial stability. Secondly, this study corroborates that timely modifications serve as a valuable tool to mitigate re-default risk, a finding that remains consistent across different policy periods. Thirdly, a distinction is drawn between mortgagors who act strategically and those who do not. It is shown that, given the same modification type, borrowers who genuinely require a modification demonstrate significantly superior post-modification performance.

In the concluding empirical chapter, I scrutinise post-default resolutions throughout various mortgage market cycles. While the examination of post-default outcomes is not a new area of inquiry within the mortgage sector, it was initially fragmented regarding post-default exit status (Capozza and Thomson (2006), Ambrose and Capone (1998) and Phillips and VanderHoff (2004)). However, literature in this area began to consider multiple outcomes within a unified framework. The most sophisticated work in this domain has been conducted by Been et al. (2013), Chan et al. (2014) and Voicu et al. (2012). This Thesis's final study aims to bridge some existing gaps, which pertain to both modelling framework and data deficiencies. Specifically, I aim to address the following research questions:

- What are the present shortcomings in analysing post-default resolutions, primarily due to the limitations of portfolio representativeness and observation window constraints? How can we optimally offer a more comprehensive and consistent perspective?
- What are the principal determinants that influence the potential exit status from default of distressed borrowers? More specifically, has there been a temporal shift in these factors?
- To what extent do policy and economic cycles affect the post-default performance of borrowers and lenders?

I contribute to the stated research questions as follows. First, I show that some post-default determinants already analysed in previous literature keep being consistent, even if applied to a newly explored mortgage sample, as Freddie Mac data on a national scale represents. Moreover, I introduce new determinants that additionally help explaining post-default resolutions, although never used in existing literature. Second, I clearly show how the mortgage market break introduced by the subprime crisis, and the subsequent enacted policies, have affected such determinants in explaining post-default resolutions. In some cases, policy periods temporary blur the effect of post-default determinants, which return to their usual pattern once governmental programs are lifted. In other cases, some drivers are not affected by mortgage market cycle and maintain their effect throughout across all time periods considered. Lastly, some drivers are permanently affected by the breaks in the mortgage sector, and never return to their previous effect.

Although this study bears some overlap with prior empirical chapter, the phenomena under scrutiny are distinct, maintaining a clear separation from previous analyses. Specifically, I examine borrower behaviour from the initial default event to the ultimate resolution outside of default, a process that may encompass modification without going beyond its occurrence. Furthermore, whilst studies on mortgage post-modification outcomes gain relevance from the HAMP period onwards, I am able to distinctly differentiate post-default behaviour before, during, and after the financial downturn.

1.3 Structure of the Thesis

The Thesis commences with a meticulous review of existing literature, categorised according to the three research areas delineated in Section 1.2. The cited works belong to highly esteemed academic journals; however, considering the significance of government policies and international standards in this field, the literature review also encompasses publications in institutional journals. The comprehensive survey of existing literature facilitated a profound comprehension of the most relevant subjects within mortgage studies. Concurrently, it assisted in focusing my research on those areas of interest covered in this Thesis. Specifically, an exhaustive review has been instrumental to identify the gaps that I have exploited to frame the research questions, and to advance the empirical work undertaken in this study.

In the first study, the correlation within mortgage portfolios is scrutinised. Correlation quantifies the concurrent movement between assets during economic fluctuations. Should assets within a portfolio be perfectly correlated, their value would uniformly alter in reaction to market changes. Correlation is straightforwardly computed for marketed assets due to the known price; however, this does not extend to retail loans, which are not traded in the stock market. Consequently, correlation is often inferred from default data or loss data (Botha and van Vuuren (2010), Geidosch (2014) and Neumann (2018)). Despite the challenges in deriving it for retail portfolios, correlation retains its importance for portfolio managers as it is utilised to ascertain portfolio loss distribution and, subsequently, to deduce capital. Frequently, correlation in retail portfolios is assumed to be a static value, likely a result of the fixed value dictated by regulatory standards (BCBS (2021) and BCBS (2005)) in capital requirement computations. The opening empirical chapter investigates whether this assumption, or simplification, is indeed applicable to residential mortgages. The study broadens the scope of Cowan and Cowan (2004), encompassing several aspects such as data representativeness, time-span, and methodology, and explores the variability of correlation within the mortgage asset class, its principal contributing factors, and its effects on mortgage pricing.

The second and third empirical chapters of this Thesis examine the determinants of post-modification and post-default outcomes respectively. There was a surge in literature in this area around the time of Global Financial Crisis, which subsequently slowed down with economic recovery.

The most recent studies on post-modification outcomes are by Schmeiser and Gross (2016) and Voicu et al. (2011). These works primarily investigate the effectiveness of Home Affordable Modification Program (HAMP) introduced by the US government in 2009 to aid borrowers in financial distress. The Thesis's second empirical chapter scrutinises whether and how borrowers behaviour altered following the discontinuation of the government program in 2016. The study distinctly separates HAMP from post-HAMP period and examines if the borrower and loan attributes that positively impacted post-modification outcomes during HAMP remain significant thereafter. Of paramount importance, the study investigates the influence of modification types on post-renegotiation outcomes and their shift across mortgage market modification break.

The third empirical chapter explores a facet complementary to the preceding one, as it analyses the determinant factors that explain the final exit status following borrower's entry in default. The pioneering studies in this field were conducted by Capozza and Thomson (2006), Ambrose and Capone (1998), and Phillips and VanderHoff (2004), who first recognised the necessity of distinguishing the diverse outcomes succeeding default. Similar to post-modification literature, this topic has seen a pausing in recent years. The most contemporary studies investigating post-default include Been et al. (2013), Chan et al. (2014), and Voicu et al. (2012). Despite these authors' contributions to this research area, recent evidence remains sparse. In fact, the samples utilised in all preceding analyses do not extend beyond the early stages of the Global Financial Crisis, a period unique in many respects, particularly regarding mortgage delinquency and foreclosure. Consequently, the insights obtained from the latest literature may no longer be informative due to shifts in borrowers' and lenders' approaches to post-default resolutions. The third empirical chapter offers a fresh perspective on this issue by explicitly examining default resolutions across mortgage market breaks. Unlike the second study, it clearly distinguishes between the pre-, during-, and post-Global Financial Crisis periods.

Chapter 2

Literature Review

This section presents a review of the relevant literature underpinning this work. The chapter is segmented into three parts, each corresponding to an empirical study within the Thesis. To ensure a coherent flow of information, each part is structured as an independent section, facilitating the linkage of pertinent literature with ease. Furthermore, each sub-section employs a unique logic in associating the most significant papers with the research questions. Given that each empirical chapter does not necessarily interconnect, each literature review sub-section is organised optimally to suit the specific topic of interest.

The first subsection addresses key papers contributing to correlation area and default contagion within mortgage portfolios. The analysis commences with papers underscoring the inadequate estimation of correlation, primarily within the corporate domain where this research area has seen extensive development. The review proceeds to literature on correlation, encompassing mortgages and other retail asset classes, before transitioning to the segment of literature that scrutinises default contagion in mortgage portfolios, a field closely related, yet not identical, to correlation. The section concludes with literature on mortgage pricing practices.

The second section offers an in-depth exploration of literature pertaining to modifications within the mortgage market. The review adheres to a temporal structure, underscoring the evolution of this research area over time and its influence caused by trigger events within the mortgage industry. This review begins with early investigations into modification determinants and the profitability of renegotiations as opposed to foreclosure. It proceeds to examine determinants of modifications from various perspectives, such as socio-economic and racial factors, in addition to scrutinising the role of securitisation, a topic that remains highly debated. The section then turns its attention to post-modification literature prior to HAMP, before transitioning to the implications of HAMP. The section concludes with the key papers for our study, which also represent the most recent contributions to this research area, focusing on post-modification determinants during HAMP.

The final section of this chapter provides an overview of the literature on post-default outcomes. Even in this case, a temporal approach is followed due to the influence of the economic cycle. The subsection commences with an exploration of early research, which tended to examine post-default outcomes in isolation. The review progresses to examine the repercussions of the Global Financial Crisis, necessitating an investigation into the increasing prevalence of modifications, which subsequently become one of the potential post-default resolutions. Although there is some overlap with previous literature, this sub-chapter retains its distinct focus, enabling a more comprehensive analysis of certain papers. The section concludes with an examination of the most recent studies on post-default outcomes, which are directly relevant to the third empirical chapter.

Before delving into each subsection of the literature review, it is necessary to provide a context concerning the US mortgage market from regulatory and policy perspectives. This will primarily aid the first empirical chapter, although it is fundamental for the remaining ones too. Subsequently, we will examine the various legislations and procedures pertaining to the treatment of delinquencies and defaults, which are necessary for the second and third empirical studies.

Over recent decades, the US mortgage market has undergone several regulatory changes, influenced by both international and domestic factors. From an international perspective, although the US financial markets face less stringent regulatory pressures compared to Europe, the Basel Accords have been adopted in this jurisdiction, albeit with modifications related to scope and applicability over time. Importantly, by establishing Minimum Capital Requirements across all asset classes, international regulations have significantly impacted and reshaped the mortgage market, given the impact on the cost of capital. In 1988, the Basel I Accord (BCBS (1988), Bank for International Settlements (2023)) started to be implemented for all banks, regardless of their size and reach. Subsequently, the Basel II (BCBS (2006)) regulatory standards were introduced in 2007-2008, exclusively for the largest and internationally-active US financial institutions, while a more straightforward and customised approach was adopted for smaller credit institutions. However, the onset of the Global Financial Crisis prompted a re-evaluation of the Basel II rules, leading to the revision and eventual release of the Basel III accords. The full implementation of Basel III (BCBS (2010)) is anticipated by mid-2025.

From a domestic perspective, the Global Financial Crisis likewise constituted a watershed moment in the US mortgage landscape, thanks to the introduction of new policies enacted by the US government. The most significant was the Dodd-Frank Act (U.S. Government (2010)), which has been instrumental in ensuring enhanced consumer protection by establishing new standards and regulations for credit institutions. Regarding mortgages, this legislation introduced a set of rules, such as the Ability-to-Repay and Qualified Mortgage (QM) Rule, which requires lenders to assess borrowers' ability to repay the mortgage before origination. Furthermore, the Dodd-Frank Act intervened in mortgage servicing rules, particularly in procedures for resolving delinquencies and initiating foreclosures. The creation of the Consumer Financial Protection Bureau (CFPB) ensured the proper implementation of these new standards, compelling lenders and servicers to comply with the new requirements and significantly impacting the mortgage market as a whole.

Concerning regulation and policies related to delinquency, in 2009 the US Department of the Treasury launched the Making Home Affordable programme US Department of the Treasury (2023*b*), aimed at assisting borrowers facing difficulties with mortgage repayments to prevent foreclosure. This program was developed in response to the escalating number of delinquencies and defaults, with the Home Affordable Modification Program (U.S. Department of the Treasury (2023*a*)) serving as its foundation. HAMP's primary objective was to facilitate the renegotiation of mortgage terms for those struggling to meet their current repayment schedule, and so constitutes a key point for the second and third empirical studies.

However, in addition to centralised schemes, the existence of judicial and recourse laws for handling delinquencies and defaults is also relevant for this study, as these state-level laws affect both borrowers' and lenders' behaviour. Judicial states are those U.S. states where a lender is obliged to go through the court system to initiate the foreclosure process of a home, which generally lengthens the entire procedure. On the other hand, in recourse jurisdictions the lender, in the event of a foreclosure, can go after the borrower for any remaining balance left after the property is sold.

2.1 Mortgage Correlation

This section provides a comprehensive review of those papers relevant for the first empirical chapter. First, it begins with the broader research in the corporate loan market. Additionally, it discusses existing studies that have identified specific mortgage features as triggers for default contagion. Lastly, it introduces relevant academic papers that have explored mortgage pricing.

The hit of Great Financial Crisis raised questions on the validity of correlation values and on the methodological assumptions set by either BCBS (2005) or alternative risk assessment frameworks. Literature and studies on this topic has grown bigger, with a particular focus on corporate asset classes or securities, leading to a widespread consensus on the lack of understanding of correlation risk (Nickerson and Griffin (2017), Chamizo et al. (2019), Chernih et al. (2006), Adams et al. (2017)). Nickerson and Griffin (2017) revise the assessment of default correlation for structured portfolios, finding that even estimating their model on pre-crisis data, the correlations used by rating agencies for CLOs were lower than those obtained by their model. Additionally, the authors argue that a commonly assumed lesson from the financial crisis is the lack of understanding of default correlations, and despite a significant period of massive defaults, limited academic work has been carried out to understand default correlations for structured products. Similarly, Chamizo et al. (2019) points out that a deficient modelling of correlation under stress could have been the cause of the failure of pre-crisis stress tests to detect the vulnerabilities of financial systems. A comprehensive work was also done by Chernih et al. (2006), who compare asset correlations calculated on monthly asset value with both Basel II and previous literature. The authors find that their results align with previous literature, while a notable discrepancy emerges when compared with Basel II and major software providers. Adams et al. (2017) explore correlation breaks among daily returns and argue that correlations are constant over time, but financial shocks lead to breaks that cause a shift in correlation level. All these studies highlight the necessity to better explore the role of correlation across different asset classes, as the Great Financial Crisis highlighted a flaw in risk assessment frameworks to correctly measure contagion effect. Nonetheless, mortgage correlation studies are quite limited in the current literature despite the relevance of this asset class in banking books and securitised markets.

Predominantly, the literature cited concentrates on corporate portfolios, with scant research conducted on mortgages. A prevalent misconception about the correlation of residential mortgages is its perceived stability. This leads to the assumption that the value set by BCBS (2005) is universally applicable to any capital calculation, inclusive of internal capital allocation. Despite the widely accepted premise of conservatism, which Hull (2015) challenges, there is limited evidence in previous studies regarding the flat nature of correlation for residential mortgages. This paucity of research is largely due to the difficulties in quantifying mortgage correlation, as its asset value cannot be directly measured. For instance, a study of Duellmann et al. (2010) investigates whether it is more effective to estimate asset correlation from stock prices or default rates. The authors recommend utilising stock prices over default rates when market price time series are available, arguing that the latter often tend to underestimate and is frequently characterised by sparse data. This conclusion diverges from Frye (2008), who rather suggest to estimate asset correlation from historical default rates, and from recent analysis by Blumke (2018) who prioritises default data over stock market data for banks and other sectors. Besides validating the superiority of correlation estimated by default rates, Blumke (2018) also demonstrates that for homogenous industry segments, the asset correlation can potentially exceed Basel regulatory values, in line with already mentioned literature. Despite this ongoing debate, it is an established fact that for retail exposures, such as mortgages, only one option is viable: to rely on default data.

Research on mortgage correlation typically utilises this approach (i.e. default or loss data), with a primary emphasis on evaluating the appropriateness of Basel assumptions. As previously noted, the correlation value stipulated in the regulatory framework is a static 15% for residential mortgages and 4% for credit cards, consistent with BCBS guidelines (BCBS (2021)). The process by which retail asset correlation for capital requirements was determined by BCBS (2021) is not explicitly detailed in the Basel accords, nor is the methodology publicly accessible due to the sensitive nature of banking industry data employed for the analysis. However, a substantial body of both early and recent literature is dedicated to scrutinising the accuracy of these values, frequently concluding that they are relatively conservative. Early studies are defined as those examining correlation in mortgage portfolios (or, more broadly, retail portfolios) prior to the Global Financial Crisis, while recent literature investigates the same issue after the financial downturn.

Among the earliest notable studies, Calem and Follain (2003) examined the validity of a 15% correlation for Single-Family residential mortgages in the US. Initially, the authors estimated capital allocation using the most recent credit risk models for mortgages available in the sector, calibrated with industry data. Subsequently, they re-engineered the asset correlation parameter to match the capital allocation suggested by the Basel formula with their initial inference. Employing this two-step approach, Calem and Follain (2003) provided evidence that *"[..] an asset correlation with a fixed* *value of 15 percent is reasonably consistent with the available evidence for U.S. residential mortgages"*. Later studies continued to assess the validity of Basel parameters in the retail sector. For example, Botha and van Vuuren (2010) analysed charge-off information loss data derived from the 100 largest US banks across various retail asset classes, such as residential mortgages, qualifying revolving and other retail. The authors determined empirical asset correlation by utilising Vasicek and beta distributions to reverse the Basel equation, evaluating the robustness of each distribution and comparing the outcomes with the benchmark value. In addition to confirming the superior fit of Vasicek distribution, the authors displayed that empirical correlations derived from gross loss data are lower than regulatory benchmarks across all analysed asset classes. A study of a similar nature was conducted by Rösch and Scheule (2004), who also used charge-off rates disclosed by US commercial banks across retail credit asset classes from 1991 to 2001. The authors examined several combinations (i.e., constant/time-varying probability of default) to deduce correlations from loss data and contrast them with the Basel benchmark. In agreement with Botha and van Vuuren (2010) but in opposition to Calem and Follain (2003), Rösch and Scheule (2004) concluded that regulatory asset correlations are significantly higher than those empirically derived. The final study in the early literature on correlation is Crook and Bellotti (2009), who focused on correlation in UK credit cards portfolios. In this instance, the authors inferred asset correlation from defaults, rather than from charge-off data, and similarly found that the Basel parameter is much more conservative than the value observed empirically.

The suitability of the Basel asset correlation for retail portfolios continued to be scrutinised even after the 2008 financial crisis. Geidosch (2014) and Neumann (2018) continued this line of enquiry, utilising fresh data and implementing more advanced methodologies. Geidosch (2014) examined correlation of residential mortgages using RMBS data, even incorporating toxic RMBS transactions. The author utilised various estimation methodologies - SFGC, methods of moments, maximum likelihood estimation, and a parametric approach - and consistently found the inferred correlation to be considerably lower than the Basel parameter, even when incorporating exceptionally low-quality transactions. Neumann (2018), however, arrived at a somewhat divergent conclusion. Utilising UK and US loss data to deduce residential mortgage correlation, the author employed a non-Gaussian, non-linear state space model, and suggested that previous findings, which emphasise the over-inflation of Basel parameters, may overlook potential biases arising from small sample sizes or non-Gaussian risk factors. Contrary to Geidosch (2014), Neumann (2018) demonstrated that the Basel correlation parameter is appropriate for both UK and US mortgages.

Literature on correlation in retail portfolios presented so far has a common denominator, i.e. looking at the asset class as a whole. Within pre-crisis literature, however, the study by Cowan and Cowan (2004) offers a unique perspective on this matter. This pioneering work delves into a more detailed analysis of mortgage correlation, starting from the intuition that this parameter may not be homogenous within a single portfolio. The authors initially segment the portfolio based on various loan and borrower characteristics (e.g., credit score, property type, occupancy), utilising quantiles for continuous characteristics and inherent categories for categorical ones. Subsequently, they extracted correlation from the default rate time series within each segment. Cowan and Cowan (2004) conclude that the correlations for the portfolio under consideration would be negligible until the book is divided into risk groups. This finding is particularly significant as it offers valuable insights into previous findings related to very low correlation values observed in retail portfolios. Despite its rich and informative content, Cowan and Cowan (2004) study has potential areas for enhancement. Primarily, the employed data originates from a single subprime lender, necessitating further analyses to validate the generalisation of the results. Additionally, the data covers only six years and is antecedent to the Global Financial Crisis. Nevertheless, Cowan and Cowan (2004) research inspired the first empirical chapter of this Thesis, which builds on their observations and significantly extends the work. The Thesis utilises loan-level data from multiple financial institutions, not limited to a single subprime lender. It leverages the Global Financial Crisis as an effective analysis laboratory, given the concurrent defaults within the sector. Contrary to Geidosch (2014) and Neumann (2018), this work employs a distinct methodology, using copula models to derive correlations from default data (as in Lee et al. (2021) and Botha and van Vuuren (2010)). Despite some criticism of these models (Egami and Kevkhishvili (2017)), their limitation in computing correlation is acknowledged. However, they are used primarily to derive a correlation indicator that demonstrates heterogeneity and sensitivity to portfolio composition.

In a parallelism with Cowan and Cowan (2004) within the corporate universe, further research has scrutinised the correlation's dependence on firm characteristics. For example, Lopez (2004) explores the empirical link between average asset correlation, a company's likelihood of default, and asset size. While their attention is primarily on the corporate sector, their findings hold relevance to our research. The empirical results suggest that average asset correlation escalates with asset size. In simpler terms, as companies augment the book value of their assets, the correlation with the economic environment also increases. Comparable findings are reported by Duellmann and Scheule (2003), who investigate asset correlation and its dependence on company size and likelihood of default, identifying a substantial relationship with both elements. Even though the study is confined to German companies, this discovery strongly aligns with Lopez (2004), hence unveiling the role of asset size in correlation. While our research focus diverges in terms of asset class, we demonstrate that mortgages with larger balances are more susceptible to the systemic risk factor and experience higher contagion.

The Global Financial Crisis has markedly influenced mortgage performance, serving as a catalyst for further analyses. A considerable body of academic literature post-crisis has emphasized the significance of particular characteristics in explaining not only the escalation in mortgage delinquency but also default contagion during economic downturns, a concept closely related to correlation. Therefore, it is crucial to also encompass this aspect of mortgage-related literature, as it sheds light on the factors that drive simultaneous default in mortgage portfolios, which may be relevant to this analysis.

A collection of studies (Gupta and Hansman (2022), Goodstein et al. (2017) and Guiso et al. (2013)) scrutinises the determinants of borrowers' choices, with an emphasis on the factors influencing strategic default and its clustering. Gupta and Hansman (2022) and Guiso et al. (2013) reveal a significant connection between leverage and default. Specifically, Gupta and Hansman (2022) delves into the defaulting behaviour of highly leveraged borrowers when house prices fall, distinguishing between moral hazard (where leverage increases the likelihood of default) and adverse selection (where high-risk borrowers prefer high-leverage mortgages). Although we cannot separate these two triggers, we also emphasize the impact of updated loan-to-value ratio (LTV) on default contagion. We further corroborate the significance of other elements, such as balance, income, and FICO scores. In addition, while Gupta and Hansman (2022) study is confined to non-agency option adjustable-rate mortgages (ARMs), we employ a more representative sample of the US mortgage market. Guiso et al. (2013), on the other hand, utilise survey data on strategic default to unfold the link between default and its strategic trigger. The authors identify the primary reasons for strategic defaults as being both economically and socially driven. Factors such as negative equity, relocation costs, and financial stability fall into the former category, while moral and social determinants, along with awareness of other people having defaulted, fall into the latter. Interestingly, Guiso et al. (2013) most notable finding is that non-recourse laws have little impact on the choice of strategic default. This behaviour is attributed either to the fact that individuals possess no other assets beyond their homes (thus offsetting the distinction between recourse and non-recourse practices) or that they are uninformed about the legal status of mortgages in their state. Ghent and Kudlyak (2011) complement the preceding analysis by examining both privately-held and GSE securitised mortgages, demonstrating that recourse laws only affect default rates by diminishing borrowers' sensitivity to equity shortfalls. This is found to be true for privately-held portfolios, but the same hypothesis cannot be dismissed for GSE loans. Although correlation does not equate to default, we observe that mortgages in non-recourse states show higher sensitivity to economic shocks, conditional on several other mortgage characteristics. From a different perspective, Goodstein et al. (2017) investigates the contagion effect among strategic defaulters, which results from escalating delinquency within the same ZIP code area. Once again, negative equity is identified as a significant driver, echoing Gupta and Hansman (2022) findings, but the authors also underscore the role of delinquency rates by geographic areas in triggering increased default contagion. Similarly, our first empirical study explores mortgage contagion implied by default experience, albeit without focusing on strategic and not-strategic behaviour, as we adopt the lenders' perspective that is blind to this aspect, and by incorporating a broader range of covariates to estimate correlation simultaneously.

In their attempt to explain the factors contributing to the escalation of defaults during the Global Financial Crisis (GFC), Mian and Sufi (2009) and Arentsen et al. (2015) highlight the intensification of lending to high-risk borrowers as a primary catalyst. Arentsen et al. (2015) attribute the surge of subprime mortgage defaults to the augmented issuance of CDS, whereas Mian and Sufi (2009) correlate the rise in mortgage defaults to excessive lending in subprime ZIP code areas. These conclusions support the notion that the 2009 economic downturn may also be explicated by credit expansion to high-risk borrowers. Our study builds on these findings by suggesting that current regulations may have generated an incentive to augment banks' portfolio correlation (and risk) for more efficient capital utilisation, by broadening credit allowance to risky borrowers whilst adhering to international standards. Contrarily to Mian and Sufi (2009), who aggregate default rates by ZIP codes (similar to Goodstein et al. (2017)), we refrain from any data aggregation and, instead, maintain the unique combination of mortgage characteristics at the borrower level. Furthermore, the authors do not quantify the variance conditional on other drivers, an issue we address in our research by estimating correlation patterns.

The final thread of literature pertinent to this study comprises recent investigations into mortgage pricing practices, often in relation to securitisation. Specifically, McGowan and Nguyen (2023) illustrate the link between foreclosure laws and lenders' decisions to either securitise or price regional credit risk, in instances where securitisation is unfeasible. The authors leverage the inherent difference between mortgages in judicial and non-judicial states; the former are linked to higher credit risk due to elevated administrative and legal costs upon foreclosure. This helps to explicate lenders' choice of either selling the loan to a Government-Sponsored Enterprise (GSE) or pricing this credit risk into the mortgage interest rate. This insight complements the findings of Hurst et al. (2016), who revealed that despite substantial regional variations in default rates, GSE mortgage interest rates do not vary based on location, unlike privately securitised ones. Both these discoveries are instructive for our research, demonstrating that mortgage pricing is also influenced by less apparent determinants. We further broaden this research area by examining the impact of correlation on mortgage pricing, which is not exclusively shaped by regional characteristics.

This latter study into mortgage pricing and its interrelation with correlation offers insights into previously unexplained pricing trends associated with recent risk-retention requirements, partially clarified by Krahnen and Wilde (2022) and Furfine (2020). Risk retention has been encouraged post the Global Financial Crisis, given that both lenders and securitisation sponsors displayed lack of motivation in adequately scrutinising loan applications, due to the transfer of credit risk to the secondary market. In response to this issue, risk retention regulation was enacted as part of the Dodd-Frank Act (U.S. Government (2010)) and the Capital Requirement Directive CRD IV (European Parliament and the Council of the European Union (2013)), in the US and Europe, respectively. As an aspect of risk-retention, loan originators are obligated to retain a portion of the default risk of loans potentially securitised on their balance sheet. This stipulation has led to various implications, one of which is mortgage pricing. Furfine (2020), for instance, demonstrates that risk retention results in considerably higher interest rates, lower loan-to-value ratios, and lower debt-to-income ratios, hence making retained loans less risky on originators' balance sheets, but more expensive for borrowers. Conversely, a more recent study by Krahnen and Wilde (2022) examines the different risk-retention practices between the UK and the US, indicating that a certain degree of opacity exists in the securitisation market, particularly concerning the suitable level of actual risk retention. By exploring the role of correlation pricing for securitised mortgages, the first empirical chapter aids in revealing less obvious practices carried out by lending institutions.

2.2 Post-Modification Resolutions

This section provides a review of the papers relevant for the second empirical chapter. First, it starts with early studies on post-modification resolutions. It then covers the introduction of Home Affordable Modification Program (HAMP) and its impact on various aspects of mortgage renegotiation practices, to then conclude with relevant academic papers that explore post-modification in the immediate aftermath of HAMP implementation.

When borrowers encounter difficulties with mortgage repayments, modifying or renegotiating the contractual terms can be offered as an alternative to foreclosing. The practice of renegotiation was not commonplace until the advent of the Global Financial Crisis. Historically, lenders showed a preference for foreclosure over renegotiation, either perceiving the former as more profitable (Wang et al. (2002)) or due to information asymmetries (Adelino et al. (2013)). Adelino et al. (2013), for instance, points out to self-cure and re-default risks as detrimental factors that prevent modifications, favouring foreclosure. Conversely, an early study from Ambrose and Capone (1996) demonstrated the existence of alternative options to foreclosure, such as forbearance and modifications, which can be beneficial to both the borrower and the lender, who ultimately does not have to carry the cost of a negative property equity.

Nonetheless, the advent of the subprime mortgage crisis, originating from the mortgage market, profoundly transformed the approach towards managing delinquent borrowers, challenging even the profitability of foreclosure. By examining non-agency securitised loans that became delinquent immediately prior to the crisis, Maturana (2017) discovered that mortgage modifications substantially mitigated the ultimate losses, particularly during periods of escalating delinquency. The significant increase in mortgage arrears necessitated a different response from lenders, thus encouraging the investigation and adoption of alternatives to foreclosure. As a result, modification rates rose sharply, and the literature on mortgage renegotiation expanded significantly, along with many other topics related to the residential mortgage market.

Existing research on mortgage modifications can be broadly categorised into two principal domains. The first examines the determinants of modifications, specifically the factors influencing lenders' or servicers' decisions to grant changes in contractual terms to distressed borrowers. The second domain explores the outcomes following modification. In both instances, the period under examination is crucial, as significant changes have transpired due to the implementation of U.S. government programs aimed at consumer protection.

The first strand of literature examining the determinants of modification has been explored by Danne et al. (2016) and Been et al. (2013). Danne et al. (2016) emphasise that borrower's characteristics hold more significance than those of the loan in securing a permanent modification, as well as in fully repaying the loan post-modification. Among these factors, income, household leverage/expenditure, unemployment and divorce are correlated with lower modification probabilities and diminished repayment success. However, utilising Irish mortgage data, these findings prove challenging to generalise across different jurisdictions. Been et al. (2013) identify a diverse array of loan, property, and neighbourhood characteristics that influence loan modification versus cure or liquidation. The current loan-to-value, neighbourhood house prices, and certain perilous loan features (e.g., ARM, interest only) emerge as strong drivers of modification determinants. Contrary to Danne et al. (2016), the data Been et al. (2013) utilise pertains to the U.S. market, albeit not entirely representative of the whole country as the mortgages are solely based in New York state. Particularly for neighbourhood characteristics, these results thus offer limited applicability.

A portion of the literature examines socio-economic determinants contributing to modification eligibility and other forms of post-default resolutions. For instance, Boehm and Schlottmann (2020) note that factors such as education, internet access, and financial experience facilitate easier access to modifications. They further observe that certain racial minorities, including African Americans, Hispanics, single women, and recent immigrants, face challenges in securing a modification. This finding contrasts with the work of Been et al. (2013) and Collins et al. (2015), who find no substantial variations in modification types across borrowers. In fact, these researchers discover that Black, Hispanic, and Asian borrowers receive marginally larger reductions in monthly payments than their non-Hispanic White counterparts in similar situations. Voicu et al. (2012) extend this discussion by investigating mortgage product features and borrower demographics as influential factors in post-default resolutions. For example, the authors find that ARM, interest-only, low or no documentation mortgages are less likely to be cured, while they are more probable to enter foreclosure and to be repossessed.

A separate stream of research examining the determinants of renegotiation has explored variations in modification practices, with a particular emphasis on the role of securitisation. Agarwal et al. (2011) draw a comparison between bank-held and securitised mortgages, discovering that the latter are less frequently renegotiated and are generally less efficient. This discrepancy is attributed to the unavoidable frictions in securitisation between servicers and investors, a phenomenon not seen in bank-held mortgages. This conclusion aligns with the findings of Piskorski et al. (2010) and Kruger (2018). Piskorski et al. (2010) compare securitised and non-securitised mortgages with similar characteristics and show that securitised loans are less likely to be modified. In addition, the gap is even wider for borrowers with high credit quality. More recently, Kruger (2018) utilises the halt in private mortgage securitisation to corroborate this concept. Utilising a longer time series that spans the Global Financial Crisis, the author shows that the same effect (i.e. securitised mortgages being less frequently modified) persists even after the introduction of government programs aimed at increasing modifications, albeit this phenomenon was partially mitigated. Conversely, Piskorski et al. (2010) and Kruger (2018) findings conflict with Ghent (2011) and Adelino et al. (2014), who both contend that there is no significant difference in modification rates between securitised and portfolio mortgages. For example, Ghent (2011) explores concessionary modifications during the Great Depression for mortgages issued in the state of New York and concludes that securitisation did not obstruct modifications, even in the 1920s. Despite the considerable difference in the mortgage market under examination, the author argues that the advantage of using such a sample is the absence of endogeneity, due to the rare rate of securitisation, and the similarity in lenders' responses to distressed mortgagors. Aligning with Ghent (2011) is Adelino et al. (2014). Adelino et al. (2014) develop an instrumental variable strategy to discern the relationship between securitised mortgages and their likelihood of being modified or foreclosed. In response to Piskorski et al. (2010), the authors demonstrate that securitised mortgages are, in fact, more likely to be modified by servicers. Part of the above findings attribute the different modification rate to the information asymmetry between borrowers, servicers and investors. Closely related to this research vein, Conklin et al. (2019) continue to probe the role of information and interest asymmetries, concentrating on the relationship between the originator and servicer. They discover that a closer relationship between these two parties decreases the likelihood of returning to a severe delinquency status within 12 months of debt renegotiation.

Each of these studies, while essential in establishing the foundation of our analysis, either treats modification as a potential resolution subsequent to default, or investigates variations in renegotiation practices. Our focus, however, is on post-modification workouts, a topic only marginally touched by these authors that we instead expand in the next paragraph.

Quercia and Ding (2009), Haughwout et al. (2009), Goodman et al. (2011) and Goodman et al. (2013) pioneered the analysis of post-modification outcomes in residential mortgages. Through the examination of non-prime loans from private-label securitisation, Quercia and Ding (2009) investigated the 12-month re-default rate, finding that substantial payment reductions, coupled with principal reduction, significantly diminish re-default rates. Recognising the early nature of their study, the authors acknowledged that their sample and time-frame may necessitate further scrutiny to confirm the significance and stability of their findings. Haughwout et al. (2009) conducted a parallel study, focusing on seriously delinquent borrowers and payment relief, whether achieved via principal or interest reductions. They noted a similar trend, where re-default rates decreased with increasing payment relief, but found this to be more effective when accomplished through principal forgiveness rather than lower interest rates. This finding is also supported by Goodman et al. (2011) and Goodman et al. (2013), who highlight the factors that determine a successful modification are related to early intervention, significant payment relief and a principal reduction, where this latter improves borrowers' home equity. It should be noted that the mortgages analysed in both studies were either subprime (Haughwout et al. (2009)) or part of private-label securitisation (Goodman et al. (2011) and Goodman et al. (2013)). A comprehensive study by Agarwal et al. (2010) underscored two crucial aspects subsequently addressed by the Home Affordable Modification Program (HAMP). Firstly, the pivotal role of affordability in re-default after modifications was emphasised, with a statistically and economically significant association found between decreases in monthly payments and a lower likelihood of re-default. Secondly, the authors ascertained that the practices of servicer modification are instrumental in determining post-modification outcomes, to such an extent that they can offset variations arising from borrower and loan characteristics, which also serve to explain post-modification behaviour.

As Agarwal et al. (2010) anticipated, the Home Affordable Modification Program (HAMP) marked a significant turning point in the U.S. mortgage market, particularly with regard to renegotiation. This government initiative, launched in 2009 and concluded in 2016, aimed to assist mortgagors struggling with repayments by establishing standards for loan modifications. HAMP, a component of the Making Home Affordable (MHA) program under the Trouble Asset Relief Program (TARP), was designed to strengthen the fragile financial sector in the aftermath of the Global Financial Crisis (GFC). HAMP provided eligible borrowers with the opportunity to modify their mortgage contracts to make payments more affordable and sustainable in the long term. This was achieved through interest rate reduction or fixing, principal amount decrease, or term extension. The program was structured to incentivise borrowers, servicers, and investors to embrace successful modifications, thus circumventing reluctance to alter mortgage terms. Eligibility for HAMP modification required mortgages to meet specific criteria relating to origination date, occupancy, balance, and debt-to-income ratio (Agarwal et al. (2017)). Consequently, not all loans were entitled for modification under HAMP, although the program effectively encouraged mortgage modifications beyond HAMP eligibility as a viable alternative to early foreclosure.

The body of literature concerning mortgage modification following the launch of HAMP can be broadly categorised into two streams. The first stream investigates the efficiency of HAMP from a policy perspective, emphasising the crucial role of servicers in its successful implementation. For instance, Agarwal et al. (2017) mainly concentrate on the impact of HAMP on servicers' renegotiation decisions, as well as the role of intermediaries in the modification process and its final outcome. Employing a difference-in-differences analysis, the authors highlight the significance of efficient servicers in managing successful modifications.

The second strand of literature, which is our focus, augmented research on post-modification outcomes, owing to the novel standardisation of mortgage renegotiations diverging from the pre-HAMP era. The implications of HAMP have been meticulously examined by Schmeiser and Gross (2016), Voicu et al. (2011) and Scharlemann and Shore (2016). Voicu et al. (2011) were the first to investigate the program's impact on post-renegotiation outcomes. Utilising a hazard model to forecast re-defaults, they discovered that borrowers who received HAMP modifications have had greater success in maintaining current payments than those who did not. Despite their study incorporating a mixed sample of first lien mortgages (i.e., bank-held, privately and GSEs securitised), a recognised limitation is the restricted geographical coverage, as the mortgages under scrutiny solely pertained to New York state, analogous to Been et al. (2013). Extending Quercia and Ding (2009) work, Schmeiser and Gross (2016) examines competing outcomes post-modification, such as cure, re-modification, foreclosure, and Real Estate Owned (REO). They too find that the most important measure of modification success is principal reduction, coupled with a decrease in total payment and interest rates. Consistent with Voicu et al. (2011), they also report HAMP modifications outperforming non-HAMP, thereby validating the program's efficacy. Among mortgage features, the authors mark the connection between high CLTV and an elevated likelihood of re-defaulting, even post-modification. However, Schmeiser and

Gross (2016) study is limited by its exclusive focus on subprime borrowers, who may not accurately represent the majority of US mortgagors presently or historically.

A further element of the HAMP initiative was the Principal Reduction Amount (HAMP PRA), designed to aid borrowers experiencing negative equity. Scharlemann and Shore (2016) examine the advantageous effects of this form of modification, which permitted a portion of the decrease in housing wealth to be transferred to lenders, simultaneously enhancing household balances. Despite Fannie Mae and Freddie Mac loans being ineligible for HAMP PRA, these two agencies also provided support to underwater borrowers through the Home Affordable Refinance Program (HARP), facilitating refinancing for underwater and near-underwater homeowners. In contrast to HAMP, borrowers eligible for HARP were required to be current with their payments. An analysis of data from Freddie Mac by Zhu et al. (2015) reveals significantly lower default rates for loans that received larger reductions in payment, with a 10% decrease reducing expected defaults by 10–11%.

Although the studies just presented scrutinise the determinants of successful post-modification outcomes, two primary areas remain unexplored in the current literature. Firstly, the effect of modifications on conventional mortgages has been less examined, as the bulk of referenced studies predominantly focuses on subprime borrowers. While these borrowers constitute the riskiest segment, and thus are of significant concern, they cannot be regarded as entirely representative. Consequently, understanding how renegotiations have shaped and influenced one of the largest segments of the US mortgage market, whose performance significantly impacts the financial system's stability, becomes essential. It is acknowledged that the sample in Voicu et al. (2011) encompasses both conventional and non-conventional loans. However, their analysis is confined solely to New York City, which boasts unique characteristics. Additionally, while many studies assess the importance of principal reduction for a successful modification, this measure was not applicable to GSE mortgages. Therefore, understanding the effect of those measures only available for GSE mortgages, is vital.

The second research gap we aim to address concerns the repercussions of amendments in the post-GFC landscape. The termination of the HAMP program did not entirely halt mortgage renegotiations; these continued to be available to distressed borrowers, even during economic recovery. For instance, Fannie Mae and Freddie Mac instituted the Flex Modification Program (see Federal Home Loan Mortgage Corporation (FHLMC) (2024) and Federal National Mortgage Association (FNMA) (2024)) to maintain assistance for borrowers struggling with monthly mortgage payments. Consequently, the second empirical chapter seeks to ascertain if mortgage modifications remained successful over the long term, once established as a viable foreclosure alternative within the mortgage system. To date, only Scharlemann and Shore (2022) has examined the post-HAMP period. However, their focus is on the incremental interest rate reset five years post-loan modification, which is only applicable to mortgages modified during HAMP. Our objective diverges, as we strive to comprehend modification efficacy following the cessation of government subsidies. A recent paper from Calem et al. (2021) also adds to the current literature on mortgage modifications, analysing the disparity in re-default rates between matching modified and self-cure loans. The authors utilise a mixed sample and distinguish between privately securitised, agency securitised, bank-held conventional mortgages, and government-insured mortgages, to accommodate potential variations in servicing practices. However, even in this case, the focus is different from our research objectives.

Lastly, our analysis extends to the COVID-19 pandemic period, which presented a unique challenge for mortgage holders. The literature on the pandemic's impact on mortgages includes several studies on the Coronavirus Aid, Relief, and Economic Security Act (CARES Act). The CARES Act (*Coronavirus Aid, Relief, and Economic Security Act, H.R. 748, 116th Cong. (2020)* (2020)), enacted in March 2020, was an economic stimulus from the U.S. Government aimed at mitigating the economic fallout of the pandemic. It introduced a range of measures to safeguard consumers and businesses, including a foreclosure moratorium[1] to support mortgage holders. This

[1] The relevant sections for mortgage obligors are: Sec. 4022. (Foreclosure moratorium and consumer right to request forbearance.) and Sec. 4023.(Forbearance of residential mortgage loan payments for multifamily properties with federally backed loans.).

moratorium permitted mortgage forbearance requests, i.e., temporary suspensions of mortgage payments, for up to 180 days, initially set to expire in February 2021[2]. Some CARES-related studies examined the strategic use of forbearance (Loewenstein and Njinju (2022) and Anderson et al. (2022)), while others (McManus and Yannopoulos (2021), Goodman and Zhu (2023) and Shi (2022)) investigated borrower and loan characteristics that increased the likelihood of forbearance. A final group of studies explored how borrowers could (or couldn't) exit the payment suspension (Shi (2022) and Cherry et al. (2021)). Despite forbearance differing from mortgage modification in its requirement for minimal documentation (Anderson et al. (2022)) and its temporary nature, an investigation into the CARES Act period could illuminate on mortgagors effectively needing a significant restructuring of contractual terms. Unlike the pre-CARES period, where temporary payment relief was not available, modelling the modifications granted during the CARES Act could help distinguish strategic borrowers from those genuinely in need of modifications.

2.3 Post-Default Resolutions

The literature concerning post-default mortgage outcomes has developed over time, owing to considerable changes in the mortgage market and significant policy interventions subsequent to the Great Financial Crisis. In this section, we offer a systematic review of the most salient papers relevant to this field of study and our research queries.

Prior to the early 2000s, post-default outcomes studies were relatively sparse, as academic inquiry primarily focused on identifying the determinants of default (Mian and Sufi (2009), Elul et al. (2010), Ghent and Kudlyak (2011), Campbell and Cocco (2015), and Gerardi et al. (2018)), a subject that retains its significance in the present day. However, given the complexity of the mortgage foreclosure process and its transition through various stages, a richer understanding of post-default dynamics began

[2] In February 2021, the forbearance period for homeowners with federally-backed mortgages was extended until June 30, 2021. This was further extended until September 2021. Federally-backed mortgages include loans guaranteed by Fannie Mae, Freddie Mac, FHA (Federal Housing Administration), VA (Veterans Affairs), and USDA(United States Department of Agriculture).

to emerge. A cohort of early studies tried to scrutinise post-default pathways from a cost-efficiency perspective or through the lens of lender strategies, placing emphasis on foreclosure. For instance, Ambrose and Capone (1998) were the first to explicitly differentiate between default and foreclosure. In the realm of mortgage pricing models, the authors challenged the conventional assumption that all defaults inevitably lead to foreclosure. They also made distinctions between trigger-event (e.g., divorce, job loss) and ruthless defaulters in post-default resolutions, extending the discourse beyond the sole determinant of negative equity. Moreover, an earlier study by the same authors (Ambrose and Capone (1996)) examined the profitability of alternatives to foreclosure for mortgage lenders. Capozza and Thomson (2006) sought to understand the transition to cure/REO for delinquent subprime loans, as well as the duration of this transition period. The authors discovered that the transition to the final outcome can be protracted, with borrowers remaining in a delinquency status for extended periods. Broadly speaking, they found that lenders are more inclined to forbear when default arises from solvency issues (as opposed to strategic defaults), or when the borrower has made some payments, or when the interest rate premium is high. They also observed that standard documentation expedites the transition to REO/cure, as more information is readily available.

Phillips and VanderHoff (2004) were among the pioneers to consolidate multiple outcomes following severe delinquency, distinguishing between three potential statuses: cure, prepayment, and foreclosure. They demonstrated that these outcomes are influenced by state-specific laws and regulations. In judicial states, where law imposes higher proceeding costs on lenders, the probability of foreclosure significantly decreases. Conversely, the decisions to cure or prepay are determined by the perceived benefits of exercising such options. However, the study by Phillips and VanderHoff (2004) utilises a relatively dated dataset of conventional loans originated between 1982 and 1988, thus it may not accurately reflect recent mortgage dynamics. Complementarily, other researchers have explored the most favourable post-default outcome, namely cure. A recent study by Liu and Sing (2018) employed non-agency securitised data from 1991 to 2007 to comprehend the driving factors behind mortgage cures. Their findings suggest that behavioural differences depend on FICO scores (with subprime borrowers posing greater risk), negative equity, and the type of interest rate (FRM or ARM).

The Global Financial Crisis significantly accelerated the development of post-default outcomes literature due to its transformative impact on the mortgage market from multiple perspectives. Notably, governmental intervention, like the Home Affordable Modification Program (HAMP), altered servicing practices and their interactions with delinquent borrowers. Consequently, a substantial portion of the literature shifted its focus towards mortgage renegotiations, either by examining this phenomenon independently or by incorporating it into the existing array of post-default alternatives. Historically, modifications were rarely treated as a possible final outcome, as they were uncommon prior to the 2008 crisis. Hence, in our analysis, we cannot avoid addressing the literature on mortgage modifications, given its substantial connection with post-default resolutions. Within this domain, some academic research has concentrated on racial discrimination and the socio-economic determinants of delinquent borrowers. Another branch has scrutinised the role of servicers and securitisation in post-default resolutions. Lastly, and most relevant to our analysis, research on the determinants of post-default outcomes is explored. We now proceed to review each of these research strands.

The literature on racial discrimination in post-default scenarios has seen substantial growth in recent years, yet there are not unilateral findings. Lauria et al. (2004) were pioneers in examining the effects of race and neighbourhood characteristics on the extent of lender assistance from default to foreclosure. They concluded that economic variables, rather than racial ones, primarily drive the foreclosure process, particularly in areas with declining property values. One possible explanation provided by the authors is that economic variables significantly differ by race, being closely correlated, which on the other hand supports our modelling choice of using only those factors that are measured by risk managers. However, the data used by Lauria et al. (2004), drawn from foreclosed mortgages in Louisiana between 1985 and 1990, may not capture recent trends or accurately represent the US mortgage market from a geographical perspective. In a more recent study, Boehm and Schlottmann (2020) investigated the influence of socioeconomic factors on mortgages nearing foreclosure and the existence of racial discrimination in obtaining a modification. They found that certain racial minorities (African Americans, Hispanics, single women, and recent immigrants) face disadvantages in securing a modification. They also identified variables such as education, internet access, and financial experience as factors increasing the likelihood of a modification. This contrasts with the findings of Collins et al. (2015), who found no significant differences in modification types among races, and even observed more generous renegotiation terms for some minorities.

A substantial body of academic literature has explored the influence of socio-economic factors on the emergence of mortgage repayment issues and their resolution. For instance, Boehm and Schlottmann (2017) scrutinise the evolution of mortgage repayment problems and potential solutions, augmenting their examination with variables such as out-of-pocket medical expenses. The study emphasises the correlation between the educational level of households experiencing mortgage difficulties and the likelihood of successful outcomes. Further research has considered the role of counselling both before and after purchase as a strategy to prevent foreclosures. Utilising a multinomial logit model, Ding et al. (2008) demonstrate that prompt delinquency counselling significantly enhances the probability of recovery among low- and medium-income delinquent borrowers. The study also reaffirms the relevance of other factors such as home equity, loan payment history (i.e. length in delinquency), local economic conditions, and borrower characteristics, all of which are pertinent to our analysis. Foreclosure counselling (and its interaction with the neighbourhood) is also at the heart of Lee (2015) on post-default resolution process. The authors reveal that the performance of the housing market also impacts the success rate of counselling. Racial characteristics of the neighbourhood increase service participation, although they diminish success outcomes. One constraint of this study is its focus on self-selected borrowers who participated in counselling activities exclusively in New York. However, whilst this information is crucial in explaining post-default dynamics, it often remains hidden from portfolio managers and could potentially overshadow a behavioural heterogeneity inherent in readily available loan and borrower characteristics.

There exist two supplementary subjects that have been rigorously examined by scholars concerning post-default resolutions, specifically regarding the dichotomy between granting modifications or initiating foreclosures. The first subject pertains to the role of servicers, while the second delves into the function of securitisation. These two areas are intrinsically linked, and have been studied both individually and collectively. Reid et al. (2017) offer one of the most comprehensive analyses on mortgage servicers and modifications, thereby supplementing the work of Agarwal et al. (2017), who were pioneers in identifying that servicer heterogeneity exists and that it accounts for the marginal positive impact of policy measures such as HAMP. Reid et al. (2017) corroborate and extend this finding using a nationwide sample of delinquent subprime loans privately securitised and originated from 2004 to 2006. The authors verify that significant servicer heterogeneity undermined the effectiveness of federal policies aimed at preventing foreclosures. After adjusting for observable risk factors, they found that cure rates differed significantly among servicers. Moreover, the scale and depth of modification efforts varied among servicers, thereby influencing the propensity to cure. The authors also highlight the need to examine banks' portfolios and mortgages held by GSEs, as their sample is confined to privately securitised Alt-A mortgages, thus limiting its representativeness.

Servicers' constraints due to securitisation is another key aspect of literature related to post-default successful renegotiations, and yet there is not a converging view. For example, Adelino et al. (2013) try to answer a common concern on the relation between securitised mortgages, contract frictions and scarce modifications. The authors do not find evidence that securitisation drove fewer modifications, and argue that contract frictions in securitisation trusts are not a significant problem. From a cost perspective, they highlight that foreclosures are also not any cheaper than modifications. Similar conclusions are reached by Ghent (2011) and Adelino et al. (2014), who both demonstrate that securitised loans have actually higher chances of being modified versus being foreclosed. On the contrary, Piskorski et al. (2010), Agarwal et al. (2011) and Kruger (2018) find that securitisation increases the probability of foreclosure and decreases the chances of obtaining contractual modifications. This is further discussed in Cordell et al. (2010;2011;), who provide an overview of different modification programs (related to loan types) and the hurdles of securitised loans being renegotiated.

Both these last two strands of discussion provide a significant viewpoint on potential mechanisms that affect post-default resolutions, particularly with respect to modifications. However, acquiring such a detailed perspective for risk management proves challenging, particularly when it comes to distinguishing post-default behaviour based on inaccessible information. Moreover, the decision-making of servicers could be influenced by the composition or risk profile of the underlying mortgages, rather than being solely reliant on their servicing practices.

We now focus on the most pertinent literature to our research, specifically studies centred on post-default outcomes and their determinants. Been et al. (2013) utilise a multinomial logit model to analyse the competing risks of modification, cure, or foreclosure following delinquency. The researchers find that both borrowers and servicers strive to minimise their losses, with FICO, LTV, and servicers being integral drivers for all potential outcomes. This comprehensive study evaluates the influence of loan, servicer, borrower, and neighbourhood characteristics on the outcome of seriously delinquent loans. However, the research has two potential limitations: it only covers mortgages in New York City, and it does not explicitly state whether overlapping policies, such as HAMP, were considered. Another notable study in this field is Chamboko and Bravo (2020), which examines mortgage status transitions, including reverse transitions, using a multi-state model on Fannie Mae mortgages observed until 2016. One possible limitation of this study is the authors' decision to exclude modifications as one of the potential statuses and to disregard the introduction of government programs. Similarly, Chan et al. (2014) investigate post-default outcomes for first-lien subprime and Alt-A mortgages originated between 2003 and 2008, with mortgages originated in New York City, akin to Been et al. (2013). The analysis is interesting as it employs a two-stage approach: initially, it transitions from delinquency to *lis pendens*[3] (among other potential statuses). Subsequently, the events following *lis pendens* are examined. The authors investigate loan characteristics, borrower behaviour, neighbourhood attributes, and racial and ethnic factors. Nevertheless, the study's scope is limited geographically and temporally, although it offers a significant foundation for further research. Drawing parallels with Chan et al. (2014), Voicu et al. (2012) utilise a two-stage multinomial logit approach to scrutinise less common factors, such as product features and borrower demographics, in explaining post-default outcomes from a subprime mortgage sample. The authors initially explore post-default outcomes, encompassing prepayment, cure, and foreclosure. Following this, they delve into foreclosure proceedings (paid-off, cure, REO, and foreclosure). In this instance, the authors utilise a large national sample of securitised loans initiated from 2004 to 2006, with the constraint of observing the sample until 2007 (excluding the post-crisis period). The authors ascertain that default resolutions vary significantly according to product features and borrower demographics. For instance, Adjustable-rate and Interest Only mortgages have a higher likelihood of entering foreclosure and becoming Real Estate Owned (REO). Junior liens possess higher probabilities of remaining in default, while owner-occupied mortgages have a higher likelihood of cure. Finally, Foote et al. (2010) probe both the borrowers' decision to default and the lenders' choice of either foreclosing or granting a modification. The authors arrive at two primary conclusions. Firstly, the borrowers' decision to default is driven by present/future income rather than the Debt-to-Income ratio at origination. Secondly, loan servicers' reluctance to grant modifications is driven by the potential negative Net Present Value that would result if the modification is granted to individuals who are likely to pay regardless. The first implication related to DTI is particularly significant, considering enacted programs (like HAMP) that use the Debt-to-Income ratio as an eligibility criterion.

The final papers discussed previously are instrumental for our analysis, as we lay our interest on post-default resolutions. However, our research aims to address certain

[3] A *lis pendens* serves as a constructive notice or warning to homeowners that property ownership is under dispute with pending litigation. It can only be filed if a claim is specifically related to the property.

unexplored areas. Firstly, the issue of temporal coverage. Recent papers do not offer a comprehensive view of the effects of implemented policies. Where they do, the authors examine modifications individually or study post-modification outcomes without providing a concurrent view that includes other potential exit statuses. We fill this literature void by providing a comparative perspective that encompasses post-default resolutions during periods of financial stability and instability, along with the pass-through of government policies. Comprehending whether the discontinuation of mortgage assistance programs has altered the determinants of mortgage post-default outcomes is critical, from both a lender and borrower standpoint. Secondly, we scrutinise prime mortgages securitised by Freddie Mac on a national scale. Most existing literature concentrates on subprime loans which, despite their significant risk, only account for an average of 12% of the mortgage market (Federal Reserve Bank of New York (2024))[4]. Therefore, studying prime borrower behaviour enhances our understanding of one of the largest segments in the US mortgage market. Finally, we augment the analysis by considering explanatory factors not thoroughly explored in existing literature on post-default resolutions, facilitated by the broad coverage of our sample permitting the exploration of state laws and additional borrower characteristics.

[4] This is an average of subprime and near-prime mortgage issuance from 2003 until 2023. Subprime mortgage issuance reached its peak in the first quarter of 2007, accounting for 26% of all originated mortgages. As of 2023, the average issuance of subprime and near-prime mortgages is 8%. For additional data, please refer to Federal Reserve Bank of New York (2024).

Chapter 3

Correlation and Residential Mortgage Defaults

3.1 Introduction

The US mortgage market has historically played a crucial role in major financial crises throughout the last century, including the Great Depression of the 1930s, the Savings and Loans crisis of the 1980s and 1990s, and the Great Financial Crisis (GFC) of 2007-2009. These crises were characterised by a high degree of correlation in borrowers' behaviour, which resulted in a significant increase in mortgage defaults. This study aims to analyse the factors that contribute to the rise in correlations in mortgage portfolios by utilizing a comprehensive loan-level database that encompasses the period of the GFC. Recent studies that focus on corporate asset classes or securities, point to a lack of understanding of correlation risk. For instance, Nickerson and Griffin (2017) argue that limited academic work has been carried out to understand default correlations for structured products. Similarly, Chamizo et al. (2019) points out that deficient modelling of correlation under stress could have been the cause of the failure of pre-GFC stress tests to detect the vulnerabilities of the financial system. Nonetheless, mortgage correlation studies are quite limited in number and scope in the current literature despite the relevance of this asset class in banks' loan portfolios and securitisation markets.

Our research contributes to the existing literature in the following ways. First, to our knowledge, we are the first to use granular mortgage loan level data with extensive coverage of the US market to study empirical correlations segmented by borrower and loan characteristics. We find that mortgage correlations appear to be highly sensitive to such characteristics. This is important because, current international bank capital regulation is based on a flat unconditional correlation in mortgage portfolios of 15%. Our results indicate that ignoring the variability of portfolio correlation and its dependence on loan and borrower factors, effectively penalises portfolios that are more diversified, i.e., with a lower average correlation. Therefore, current regulation could create incentives for banks to increase portfolio concentration which could eventually lead to greater fragility in the banking system. We quantify such incentives and show how banks could make a more efficient use of their equity capital by investing in high-correlation mortgage portfolios which would bring them closer to their regulatory capital.

Second, our methodological approach is novel. While the literature on correlation in the context of corporate exposures is extensive (Adams et al. (2017), Driessen et al. (2009), Longin and Solnik (2001), Gordy (2000), Blumke (2018)), few studies have investigated the correlation in portfolios of retail exposures. Previous studies calculated correlations among mortgages either from the prices of residential mortgage-backed securities (RMBS) (Geidosch (2014)), or from aggregate charge-off data (Botha and van Vuuren (2010)), or from loan level data obtained from specialised lending institutions (Cowan and Cowan (2004)). The lack for market prices for retail exposures implies that loan level mortgage correlations have to be calculated with loan level default/loss data. Cowan and Cowan (2004) were the first to adopt this approach. We extend their analysis by considering a sample that includes the GFC and by adopting a different methodology and a more extensive database that includes 25 million mortgages issued from 1999 to 2017 across the Unites States. Our loan level data enables us to condition our analysis on loan and borrower characteristics. Our estimation strategy employs a popular model adopted by bank regulators (BCBS (2005), Blumke (2018)) in which correlation is a key factor that drives the difference between long run default probabilities ($PD_{LongRun}$) and default probabilities in a crisis (PD_{Crisis}). Utilizing a logit model, we estimate both probabilities by exploiting the GFC as a benchmark crisis scenario. This approach allows us to identify how borrower and loan characteristics influence mortgage portfolio correlations in tranquil as well as crisis periods. Our findings indicate that mortgage correlations are primarily affected by the borrower's loan size, debt-to-income ratio, and loan-to-value ratio.

Third, we examine whether banks price correlation risk in the interest rates offered to mortgage borrowers. New borrowers who exhibit higher (lower) correlation with existing borrowers in a bank's portfolio should be charged a higher (lower) interest rate by the bank to compensate for the increased (decreased) risk of joint default in its mortgage portfolio during a crisis. Our findings indicate that while some lenders apply a positive premium for correlation risk (US Bank, Sun Trust, Provident), for others the premium is negative (JP Morgan Chase, Citi, Bank of America and Wells Fargo). Interestingly, the banks in the latter group belong to the Global Systemically Important Banks (G-SIBs). As banks exhibit a significant variation in their sensitivity toward correlation risk, we find that borrowers have the potential to save an average 4.41% on their total interest payments for a standard mortgage by "shopping around". We conjecture that a negative premium may be the result of (1) intense market competition that pushes interests down and decouple them from portfolio concentration considerations, (2) an aggressive expansion strategy by the lender to increase market share in a given market segment which would yield to the same outcome as in point (1), (3) portfolio correlation risk not being priced because mortgages would be securitised and skin-in-the-game provisions fail to generate the incentive for some banks to align mortgage prices to correlation risk (Fuster et al. (2022), Furfine (2020) and Krahnen and Wilde (2022)). Such correlation-price connection may also not be justified as Freddie Mac (Federal Home Loan Mortgage Corporation) and other agencies combine in the same securitised transaction mortgages from different banks. This potentially increases diversification of the underlying pool of loans relative to diversification in originators' portfolios. Nonetheless, recent research shows that Government Sponsored Enterprises and investors in RMBS should pay close attention to correlation patterns in the underlying pools of mortgages that may lead to higher default risk (McGowan and Nguyen (2023)).

This study analyses mortgages acquired by Freddie Mac for the purpose of securitisation. Considering that prime borrowers constitute the largest share (Adelino et al. (2016) and Federal Reserve Bank of New York (2024)) in US mortgage market, the data employed well represents the archetypal characteristics of loans and borrowers in the United States, regardless of the fact that conforming securitised loans are not retained on lenders' balance sheet. As such, the mortgages employed to draw our considerations are presumed to occupy a significant position within a typical commercial bank's mortgage portfolio. Although not wholly representative, employing this dataset offers valuable insights into mortgages dynamics through the lenses of correlation applicable to a large segment of the US mortgage sector.

The paper is organised as follows. Section 2 outlines literature on correlation to date. Section 3, presents a description of the data. Section 4 outlines the methodology employed. In Section 5, we discuss our findings. Section 6 concludes the paper.

3.2 Data

In 2021, within the US commercial banking sector, residential mortgages accounted for 23.01% of total the assets, evenly distributed between mortgage-backed securities (12.6%) and residential real estate loans (10.4%), totalling 5.27 trillion dollars (Board of Governors of the Federal Reserve System - Data (2023)). However, the size of the US residential mortgage market stretches well beyond the numbers just reported, as the largest part of originated residential mortgages is securitised and sold to Government Sponsored Enterprises (GSEs) like Freddie Mac, Fannie Mae and Ginnie Mae (66% of the total, according to Fuster et al. (2022) and Banking Strategist (2022)). Overall, the US single family residential mortgage market volume was close to $13 trillion in Q3 2022 (Banking Strategist (2022)).

This study employs loan-level and borrower-level data on 25 million fully amortizing fixed-rate, single-family mortgages. The dataset includes mortgages originating from the first quarter of 1999 through the end of 2017. These mortgages were issued by over 100 lenders and subsequently acquired by Freddie Mac for securitization purposes. The Freddie Mac data employed in this study is part of the publicly available Single-Family loan level dataset (Federal Home Loan Mortgage Corporation (FHLMC) (2022)). The active and default statuses of the loans are tracked until the second quarter of 2018. Consistent with the demographic distribution in the United States, states such as California (with over 3 million mortgages), Florida, Texas, and Illinois (each with over 1 million mortgages) have a larger representation within the sample (Figure 3.1).

Data on both origination and performance is collected for each mortgage. Origination data includes borrower-, property- and mortgage-related characteristic measured at the time of issuance. Table 3.1 presents the distribution of selected variables, including *Credit Score*, *Loan-to-Value (LTV)*, *Debt-to-Income*, *Interest Rate* and *Loan Balance*. The *Credit Score* is the FICO score, ranging from 300 to 850, with higher scores indicating a lower expected default rate. Scores below 669 are typically associated with a subprime status. *Loan-to-Value* is calculated as the ratio of the original mortgage loan amount to the appraised value of the property at the time of purchase, and ranges from 6% to 105% in our sample. The *Debt-to-Income* ratio represents the sum of the borrower's monthly debt payments, including housing expenses related to the underwritten mortgage, divided by the total monthly income used to underwrite the loan. The *Debt-to-Income* ranges from 0% to 65%. The introduction of stricter underwriting standards following the GFC is evident in the average increase/decrease of *Credit Score* and *Debt-to-Income*, respectively. This structural break in eligibility criteria is also documented by previous studies (see Furfine (2020), Floros and White (2016)). Similarly, the average *Loan-to-Value* experienced a decrease after 2009, but there has been a recent reversal in this trend, primarily due to the implementation of support schemes for homebuyers.[1]

[1] In 2014 Freddie Mac launched *Home Possible Advantage(SM)*, an affordable conforming, conventional mortgage with 3% down-payment requirement (Federal Home Loan Mortgage Corporation (FHLMC) (2014)). Similarly, Fannie Mae announced in the same year a 97% LTV mortgage for First-Time homebuyers (Federal National Mortgage Association (FNMA) (2014)).

Table 3.2 shows that the majority of borrowers purchase primary residences, while a smaller proportion buy investment or second homes. In contrast, the *Loan Purpose* exhibits an interesting increase in refinance mortgages immediately after the GFC, which can be attributed to the declining interest rate environment. On the other hand, the *Channel* variable experiences a significant decline in *Third-Party-Originations* (TPOs)[2], due to enhanced transparency and stricter reporting criteria mandated by Freddie Mac after the crisis (Federal Home Loan Mortgage Corporation (FHLMC) (2022)). With the exception of *Property Type*, which shows an increasing share in the *Planned Unit Development* (PUD)[3] segment, all other mortgage characteristics are evenly distributed over time.

Within every quarterly vintage cohort, loans performance is monitored with monthly frequency since the date of origination. *Delinquency Status*, *Interest Rate* and *Unpaid Balance* are regularly updated throughout the entire lifetime of the loan. The availability of performance variables helps us to determine the evolution of each mortgage's credit performance and collateral information. For example, by knowing *Property State* (i.e. the state or territory where the property securing the mortgage is located) we can track the changes in state-level House Price Index and thus derive *Updated Loan-to-Value*.[4] Likewise, we can calculate the *Loan Age* from origination to the latest

[2] The Channel field is set to the data value of "TPO" (i.e., Third Party Originator Not Specified) for all loans which do not specify whether they are Broker ("B"), Correspondent ("C"), or Retail ("R"). Note that prior to 2008, Freddie Mac did not collect granular information on the types of origination channels. In 2008, Freddie Mac began collecting the granular information necessary to disclose whether a Broker or Correspondent was involved in the origination of each loan (Federal Home Loan Mortgage Corporation (FHLMC) (2022)).

[3] A Planned Unit Development (PUD) is a real estate project in which each unit owner holds title to a lot and the improvements on the lot, and the home-owners association holds title to the Common Elements. The unit owners have a right to the use of the Common Elements and pay a fee to the home-owners association to maintain the Common Elements for their benefit. See Mandelker (2018) and David (2015) for details.

[4] While *Loan-to-Value* is the ratio between original loan amount on the issue date and mortgaged property's purchase price, *Updated Loan-to-Value* is the ratio between outstanding balance at time t and the updated appraisal value, where the latter is calculated based on state-level change in house

available observation of the loan.

Amongst performance variables, repayment information is crucial in determining the default status of the mortgage. Two indicators are available to monitor the repayment performance of each loan. The first indicator is the *Zero Balance Code*, which shows the reason why the loan balance has been reduced to zero, including charge-off, real estate owned (REO) acquisition[5], repurchase prior to property disposition and third-party sale. The second indicator is *Delinquency Status*, which refers to the number of days a borrower has been delinquent. Both variables are used to identify high-risk customers and trigger the default status, as the first occurrence of either 90-days delinquency or *Zero Balance Code* being populated. This aligns with the recently updated regulatory definition of default (Bank for International Settlements (BIS) (2013)). Based on this definition, 4.68% of the mortgages in our sample experienced default during the observation period. We consider the occurrence of first default as an absorbing state, and thus, we exclude any observations after the initial default occurs. Figure 3.2 and Figure 3.3 depict two complementary aspects of the evolution of mortgage defaults during our sample period. Figure 3.2 shows that the peak in defaults occurs in 2010, after the onset of the GFC. Therefore, in later analysis in this study we identify the mortgage crisis period as the years from 2009 to 2011 in order to capture the bulk of default events. The last spike we observe is due to hurricanes striking Texas (category 4 hurricane Harvey in August 2017) and Florida (category 4 hurricane Irma in September 2017). Figure 3.3 displays the default rate by year of origination, highlighting that mortgage originated just before the crisis are more prone to default. The observed default patterns are the result of the combined impact of the GFC and the natural lifecycle of mortgages. The latter is characterised by a hump-shaped default rate that peaks within the first 5 years from origination (Calhoun and Deng (2002), Xu et al. (2021) and Larson (2023)). Both of these factors are controlled for in our default models.

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prices from origination to time t.

[5] Real Estate Owned (REO) acquisition refers to foreclosed properties that are owned by the lender and were not sold at an auction.

Table 3.3, Table 3.4 and Table 3.5 provide a breakdown of the annual default rates based on borrower and loan characteristics. The default rates exhibit an inverse relationship with the *Credit Score* (Table 3.3), with subprime borrowers (scores below 669) being approximately 20 times riskier, on average, than super-prime borrowers (scores above 800).[6] The default rates for *Loan-to-Value* at origination and *Updated Loan-to-Value* (Table 3.4) align with economic intuition, showing an increase in delinquency rates as leverage increases. While *Loan-to-Value* at origination is a static field, meaning that mortgages within a particular bucket do not migrate, *Updated Loan-to-Value* is dynamic. This means that mortgages belonging to bucket i at time t can migrate to bucket j at $t+1$, depending on the ratio between the amortised balance and the updated appraisal value. The updated appraisal value is influenced by variations in the House Price Index at the state level, while the outstanding balance follows the amortization schedule. Lastly, Table 3.5 breaks down the default rate based on the main categorical variables that identify the type of buyer (first time buyer versus others), rationale behind the purchase (primary home, secondary home or investment), type of intermediary, property type, type of financing (purchase versus refinance). The Table reveals variability in default rates across these categorical variables which will be appropriately controlled for in our estimation.

One of the main objective of our study is to capture the heterogeneous change in delinquency rates between the *Long-Run* and the *Crisis* periods. This is clearly illustrated in Figure 3.4, which presents the ratio of average yearly default rate during the GFC to the average yearly default rate before the GFC, for each state. While most states experienced a twofold increase in default rates, states like California, Nevada, Florida, Arizona witnessed a sixfold default rate rise during the *Crisis* compared to the baseline. Notably, among these states, only California and Arizona are non-recourse states, suggesting that strategic defaulters may not be the primary factor contributing to the significant change in defaults observed in the GFC (see Ghent and Kudlyak (2011) and Guiso et al. (2013)).

[6] This factor is calculated as the ratio between average yearly default rates of borrowers having a score below 669 and those above 800.

To evaluate the representativeness of our sample in relation to the US market, in Table 3.6 we compare it with data from the Home Mortgage Disclosure Act (HMDA) (Consumer Finance Protection Bureau (CFPB (2022)). The HMDA database is the most comprehensive source of publicly available information on the U.S. mortgage market. Enacted by Congress in 1975, the Home Mortgage Disclosure Act (HMDA) requires many financial institutions to maintain, report, and publicly disclose loan-level information about mortgage applications. Although HMDA data does not provide complete coverage of the US mortgage market, it remains the most extensive publicly available source of loan-level mortgage data. Table 3.6 displays the number of mortgage applications and originations included in the HMDA database from 2007 to 2017. Of the 187 million mortgage applications received in that period, 48.1% resulted in originated mortgages. The majority of these applications are conventional loans (69.1%), which are the most common loan type in the US mortgage market. Conventional mortgages are not directly insured by the US Government, unlike FHA-insured[7], FSA/RHS-guaranteed[8], and VA-guaranteed mortgages[9]. Instead, they are retained on banks' balance sheets or acquired by GSEs (e.g. Freddie Mac and Fannie Mae), which are the primary participants in this market. Fannie Mae and Freddie Mac primarily acquire conventional loans not insured by the government (46.1%) and establish guidelines (conformity rules) that depository and non-depository lenders must adhere to when securitizing loans through GSEs. Conformity rules impose restrictions on loan

[7] A Federal Housing Administration (FHA) loan is a home mortgage that is insured by the government and issued by a bank or other lender that is approved by the agency. FHA loans require a lower minimum down payment and lower credit score than many conventional loan. The FHA loan is designed to help low- to moderate-income families attain home-ownership. They are particularly popular with first-time homebuyers.

[8] FSA/RHS loans are a type of financing provided or guaranteed by the Farm Service Agency (FSA)/Rural Housing Service (RHS) of the U.S. Department of Agriculture (USDA). FSA provides direct and guaranteed farm loans for farmers and ranchers of all kinds. RHS lends directly to low-income borrowers in rural areas and guarantees loans issued by approved lenders that meet RHS requirements.

[9] VA-guaranteed mortgages are loans available through a program established by the U.S. Department of Veterans Affairs (VA) (previously the Veterans Administration). With VA loans, veterans, service members, and their surviving spouses can purchase homes with little to no down payment and no private mortgage insurance and generally get a competitive interest rate.

size, credit score, down-payment, debt-to-income ratio and mortgage insurance, even though there are a lot of exceptions and compensating factors whenever some criteria are not met. While the conformity rules established by Freddie Mac and Fannie Mae do not completely overlap, they significantly impact the acceptance/rejection mechanism of mortgage applications in the broader mortgage market. Although there is no explicit market division between Fannie Mae and Freddie Mac, it is well-known that historically, Freddie Mac has targeted smaller banks and thrifts, while Fannie Mae has predominantly acquired mortgages from larger commercial banks. However, the post-GFC mortgage market witnessed numerous mergers and acquisitions among lenders, blurring the boundaries between the originators served by each agency. While Fannie Mae has a larger volume of mortgages compared to Freddie Mac, Table 3.6 illustrates that Freddie Mac still holds a significant share, of approximately 25.6%, of conventional mortgages in the US market.

3.3 Empirical Methodology

Our loan-level default probability estimates are derived using a panel-logit discrete hazard model,[10] which allows us to calculate a long-run default probability ($PD_{LongRun}$) and a downturn default probability (PD_{Crisis}) for each loan. These PDs are then used to compute loan-level correlations. We employ annual data so that the model produces 12-month PDs that can be directly used to extract implied correlations from the Internal Rating-Based approach of current bank capital regulations model (BCBS (2005)). The performance of each loan is tracked annually, and a binary 0/1 dependent variable is computed each year to flag default based on loan's delinquency at the end of the respective year. Default is triggered when the borrower is 90-days delinquent or when the *Zero Balance Code* in the Freddie Mac database is populated, as discussed in Section 3.2. The explanatory variables for each loan include time-invariant characteristics at origination (e.g. *Credit Score*, *Purpose*, *Region*[11]) and time-varying characteristics

[10] Panel logit/probit models are often used as default probability models. A similar model specification is adopted by Arentsen et al. (2015), Ghent and Kudlyak (2011) and Lee et al. (2021).

[11] To avoid excessive volatility brought by single State controls, States are grouped into Bureau of Economic Analysis Regions: New England, Mideast, Great Lakes, Plains, Southeast, Southwest,

(e.g. *Loan Age*, *Updated Loan-to-Value*). Then, a panel logit model is estimated as per Equation 3.1.

$$PD_{W_{it}} = \frac{1}{1+exp(-W_{it})} \tag{3.1}$$

with

$$\begin{aligned} W_{it} = \alpha + \sum_{b=1}^{N} \beta_b LoanCharacteristics_{b,i(t)} + \gamma Crisis_t + \\ \sum_{b=1}^{N} \delta_b Crisis_t \times LoanCharacteristics_{b,i(t)} + \zeta_z Controls_{z,t} \end{aligned} \tag{3.2}$$

where i represents each distinct mortgage in the sample observed in time t, while the index b represents each loan characteristic included in the regression. The dummy $Crisis_t$ is activated for the years running from 2009 to 2011 inclusive, as we observe that the effect of the GFC on mortgage defaults peaked during that period.[12] The subscript t for loan characteristics is in brackets to denote that only some of the characteristics are time dependent. Controls include 12 month unemployment rate as a macro factor, loan age, and fixed effects to capture unobservable factors that may influence the default probability across: (a) geographic regions in the US, (b) states with recourse versus non-recourse legislation, (c) lenders and (d) loan, borrower and property types. The explanatory power of the models is measured with rank-ordering measured such as the GINI and AUROC coefficients (Yang et al. (2023) and Zeng and Zeng (2019)). We use standard errors clustered at the mortgage level. PD_{Crisis} and $PD_{LongRun}$ are estimated by switching on and off, respectively, the crisis dummy. Then, for each combination of mortgage characteristics, we feed PD_{Crisis} and a $PD_{LongRun}$ into the asymptotic single risk factor model (ASRF) used by regulators that links PD_{Crisis}, $PD_{LongRun}$ and correlation as in Equation 3.3:

$$PD_{Crisis,i} = \phi\left(\frac{\phi^{-1}(PD_{LongRun,i}) + \phi^{-1}(0.999)\sqrt{\rho_i}}{\sqrt{1-\rho_i}}\right) \tag{3.3}$$

where $\phi(x)$ denotes the cumulative distribution function for a standard normal random

Rocky Mountain and Far West. See Bureau of Economic Analysis (2023) for state to region mapping.

[12] Among the Controls we do not include the type of financial intermediary that originated the mortgage (i.e. the origination Channel), as it is not available consistently throughout the sample period.

variable, $PD_{Crisis,i}$ is the downturn PD for mortgage i, while $PD_{LongRun,i}$ is the long-run PD for mortgage i. Upon estimating both $PD_{Crisis,i}$ and $PD_{LongRun,i}$ through Equation 3.1 by either activating the dummy variable $Crisis_t$ or not, the correlation coefficient ρ_i can be derived by numerically inverting Equation 3.3. This step constitutes the turning point of our analysis. The deduced correlation coefficient ρ_i, dependent upon the distinct combination of mortgage and borrower characteristics, represents the degree of correlation of each individual mortgage with the single risk factor which exemplifies the overall financial distress in the market.

In the second step of our analysis we investigate whether and how lenders incorporate correlation risk when pricing newly issued mortgages. We define the excess mortgage interest rate δ as the difference between each mortgage's *Interest Rate* at origination and the (quarterly) average *Interest Rate* of all mortgages with the same vintage:

$$\delta_i = OriginalIR_i - \frac{\sum_{j=1}^{N_J} OriginalIR_j}{N_J} \tag{3.4}$$

By adopting this definition, we eliminate any trends from the time series of mortgage rates. The excess mortgage interest rate is then linearly regressed against previously estimated loan-level correlations, loan characteristics, bank fixed effects, their interaction with correlation and the usual set of controls:

$$\begin{aligned} \delta_i = \alpha + \sum_{b}^{N} \beta_b LoanCharacteristics_{b,i} + \omega \times \rho_i + \sum_{f}^{M} \phi_f Bank_{f,i} + \\ \sum_{p}^{M} \psi_p Bank_{p,i} \times \rho_i + \zeta_z Controls_{z,t} + \epsilon_i \end{aligned} \tag{3.5}$$

We also test a second set of regressions in which we estimate the determinants of excess mortgage interest rates for each bank separately as in Equation 3.6:

$$\delta_{ij} = \alpha + \sum_{b}^{N} \beta_b LoanCharacteristics_{b,i} + \omega_j \times \rho_{ij} + \zeta_z Controls_{z,t} + \epsilon_{ij} \tag{3.6}$$

where, differently from Equation 4.5, δ_{ij} is the Excess Interest Rate at origination for mortgage i issued by lender j.

It should be noted that the logit regression in Equations 3.1 and 3.2, which is used to derive correlations, includes the excess mortgage interest rate as a control variable. Conversely, Equation 3.5 uses correlation as an explanatory variable to explain the excess mortgage rate. When estimating Equation 3.5, to ensure its correlation covariate is not "mechanically" endogenous, we re-estimate it with Equations 3.1 to 3.3 from a reduced sample comprising mortgages originated up to 2011 (inclusive) while excluding the excess mortgage interest rate as an explanatory variable. We then estimate the excess mortgage interest rate model with the remaining data, which include mortgages originated after 2011.

3.4 Results

3.4.1 Default Probabilities and Correlation

To derive implied correlations we first estimate PD_{Crisis} and $PD_{LongRun}$, with the multi-period logistic model introduced in Section 3.3. Marginal effects are reported in Table 3.7. The first set of models (*Model 1* and *Model 2)* only incorporates static variables, i.e. measured at origination and not changing over time. Having as a reference the observed default rates presented in Table 3.3, the economic significance of *Credit Score*, *Debt-to-Income* and *Excess Interest Rate* as determinants of default probabilities is confirmed. A decrease of 50 points in *Credit Score* leads to an increment in default probability of 54 basis points (bps), in line with average default rates observed in Table 3.3. An absolute increase of 10% of *Debt-to-Income* (e.g. from 30% to 40%) yields an increment in default probability of 28 bps. Finally, a 1% increase of *Excess Interest Rate* is associated with an increment in default probability of 52 bps. The marginal effects (and therefore, the underlying model coefficients) remain stable also in the subsequent model specifications, although they are smaller due to the inclusion of additional factors. When *Model 1* is augmented with the *Crisis* dummy, as shown in *Model 2*, we observe an increase of 1.5% in yearly default probability, in line with statistics reported in Table 3.3.

However, although variables measured at origination are important, mortgage default is also influenced by changing factors over time as indicated by the improved explanatory power of the model when these factors are introduced (*Model 3* to *Model 5*). Yearly change in unemployment rate at state level (Ump_{12}) and *Updated Loan-to-Value* are statistically and economically significant. A 1% increase in Ump_{12} yields an average increment in default probabilities of 12 bps, while an increase of 10% (e.g. from 60% to 70%) in *Updated Loan-to-Value* produces an average increment in default probability of 34 bps. With the full model, *Model 5*, we can verify that the marginal effect of each default driver is always greater in a crisis period relative to the baseline scenario.

Next, for each mortgage, $PD_{LongRun}$ and PD_{Crisis} are calculated based on the loan's characteristics. Loan level correlation ρ_i is then computed numerically for each loan by selecting the ρ_i that minimises the quadratic difference between $PD_{Crisis,i}$ and its estimate obtained from the right-hand side of Equation 3.3, which is based on $PD_{LongRun,i}$ and ρ_i. We obtain a complete distribution of correlations ρ_i, whose variability is driven by the unique characteristics of mortgage i. Results are reported in Table 3.8, which shows that the variability of correlation ranges from 0% to a maximum value of 13.07%. However, despite its variability we observe that correlation never exceeds the 15% value set by the Basel Committee on Banking Supervision (BCBS (2021)). Therefore, the benchmark set by the regulators proves to be sufficiently conservative even when covering the GFC and a large share of the US mortgage market.

Table 3.8 reports average, standard deviation and upper quantiles of the correlation distribution broken down by the most relevant mortgage features. Average correlations in Freddie Mac seem aligned with Cowan and Cowan (2004), even if slightly higher on average for the common drivers considered. In particular, we observe higher and steadily increasing average correlation as debt-to-income increases. This highlights that borrowers on conventional mortgages may be more sensitive to economic shocks, than implied by the pre-GFC analysis of subprime borrowers from a single small lender in Cowan and Cowan (2004). Moreover, unlike Cowan and Cowan (2004) who examine each mortgage dimension separately, our methodology incorporates all mortgage dimensions simultaneously. This enables us to observe trends that are driven by each risk dimension while controlling for the confounding influence of the others. Also, our sample allows us to investigate regional and lender specific risk dimensions which could not be explored with an analysis restricted to an individual lender.

Figure 3.5a reveals that mortgage correlation is proportional to loan balance. This result is consistent with Lopez (2004) who shows that average asset correlation is an increasing function of asset size for corporations. As firms increase the book value of their assets, they become more correlated with the general economic environment. Although this has never been factored into banks' regulatory capital requirements associated with holdings of residential mortgages, our results indicate that a loan-size adjustment to capital charges for residential mortgages would be appropriate. Our findings suggest that, under adverse economic conditions, borrowers with higher balances are more correlated and, as a consequence, could produce larger bank losses due to their increased likelihood of defaulting jointly.

Variability in correlation is also evident across U.S. regions, where Far-West, Rocky Mountains, New England and Mid-East stand out over the other territories (See Figure 3.5b). This is in line with the evidence presented in Figure 3.4 in which we highlight strong regional differences in the $DefaultRate_{Crisis}/DefaultRate_{LongRun}$ ratios which ultimately drive correlation. This finding aligns with research made by Hurst et al. (2016) and Mian and Sufi (2009), who highlight significant geographical variations in mortgage defaults.

Similarly, differences in correlation are found when splitting the sample by Recourse and Non-Recourse states (see Figure 3.6). Borrowers in non-recourse states experience higher correlation, and hence higher risk of joint default, which is likely linked to their incentives to "walk away" from their loans in a crisis when they experience negative equity. This confirms the findings of Ghent and Kudlyak (2011), as we demonstrate that borrowers in non-recourse states are more likely to default in adverse scenarios.

Next, we investigate how the conservative level of correlation imposed by regulators at a flat 15% may cause perverse incentives for banks to invest in high-correlation, high-risk mortgage portfolios. To do so, we compute the regulatory capital that would be applied to portfolios with different characteristics based on actual correlations and compare it with the capital obtained with the 15% correlation imposed by the regulators. For each mortgage characteristic in Table 3.8, e.g., a specific credit score, we compute "actual" capital levels by employing the 5% quantile and the 95% quantile of the distribution of implied correlations obtained for that characteristic. We then calculate the ratio of regulatory capital to actual capital. Results are reported in Table 3.9. From the last row in the Table, we can see such ratio for low-correlation mortgages (corresponding to the 5% quantile of the correlation distribution) is, on average, 15.1 across all the dimensions considered. This means that the required capital is 15.1 times larger than the actual capital of a low-correlation mortgage portfolio. It should be noted that the ratios in the last two columns of the Table do not depend on the loss given default (LGD) and exposure at default (EAD) found in the regulatory capital formula for retail exposures (BCBS (2021)) as they cancel out when the ratios are computed.

When looking at high-correlation mortgages (corresponding to the 95% quantile of the correlation distribution), required capital is 3.1 times larger than it should be, on average. This indicates that investing in high-correlation mortgage portfolios represents a major opportunity for a bank to make a more efficient use of its capital. Indeed, this type of investment would more closely align the risk profile of the portfolio to the risk profile implied by the conservative 15% corelation set by the regulators. The last column in the Table shows that a bank's actual capital would be closest to its regulatory capital, i.e. and minimise unused capital, if the bank invested in the riskiest mortgages, i.e. with very poor credit score (less than 579, with a required to actual capital ratio of 2.5), high updated loan to value (>100%, with a ratio of 2.2), high debt to income ratio (>55% with a ratio of 2.4), high balance (>$450k with a ratio of 2.1).

The riskiest regions with the lowest ratio (2.5) are the Far West and US Territories. In terms of borrower's liability, borrowers in non-recourse states are the riskiest when looking at the higher end of the correlation spectrum in that group, with a ratio equal to 2.7.

3.4.2 Correlation and Mortgage Pricing

We have determined that correlation exhibits high variability across different mortgage characteristics. We now assess how financial institutions account for correlation risk when pricing through-the-door mortgages. To achieve this objective, loan-level excess mortgage interest rates are linearly regressed on the usual mortgage factors and loan-level correlations. Differently from the panel-logit discrete hazard model that we employed to estimate default probabilities with annual data, the frequency of observations is now quarterly, and the excess mortgage interest rate is only measured at origination by design, as the sample is composed of fixed-rate mortgages.

Regression results are reported in Table 3.10. *Model 1* does not include any bank fixed effects, *Model 2* incorporates bank fixed effects, and *Model 3* also accounts for the interaction between correlation and specific lenders. Loan-level covariates are highly statistically significant and with the expected sign. Our estimates indicate that banks charge a lower mortgage rate to individuals with a higher credit score and a higher rate to those with higher loan to value and debt to income ratios. When looking at the economic significance of our findings (based on *Model 3*) a 50 point increase in the credit score lowers the excess mortgage interest rate by 9.5 bps. On the other hand, a loan-to-value increase by 10% (i.e. from 60% to 70%) determines an 6.3 bps increment in mortgage rates, while the same increment in the debt-to-income ratio yields a 2.4 bps change.

Regarding how correlation affects excess mortgage interest rates, *Model 1* and *Model 2* in Table 3.10, indicate that correlation is priced positively. However, when in *Model 3* we interact correlation with dummies that identify mortgages originated by different lenders, the sign of the interacted variables' coefficients does not remain consistently positive. Instead, the net effect of correlation on excess mortgage interest rates is negative for Bank of America,[13] JP Morgan Chase, Citi and Wells Fargo.[14] A negative effect indicates that these institutions offer reduced interest rates for mortgages associated with more highly correlated segments. This is likely because, despite these loans presenting a higher risk from a correlation perspective, they also belong to more profitable pockets, making them appealing to larger banks. As a robustness test, we also replicate the same analysis for each bank separately. Results are reported in Table 3.11. The results confirm our previous findings, with the same lenders exhibiting negative pricing for correlation. These lenders belong to the group of Global Systemically Important Banks (G-SIBs) (Financial Stability Board (2022)), which are required to hold extra capital buffers to decrease the likelihood of their default and the resulting knock-on effects on other financial institutions. As they need to comply with the conservative 15% correlation value for regulatory capital purposes, they have the incentive to maximise correlation in their residential mortgage portfolio, in order to make efficient use of their equity capital. This implies that current regulation may generate the incentive for these banks to increase portfolio concentration if this helps them exploit profitable opportunities. This tendency of increasing risk taking to boost profit without altering capital requirements, which is normally referred to as 'regulatory capital arbitrage' (Jones (2000)) is reputed to be one of the causes behind the GFC (Beltratti and Paladino (2016) and Boyson et al. (2016)). While regulatory capital arbitrage was widely documented in the context of the GFC, we would like to highlight that certain perverse incentives, originally targeted for resolution through post-crisis regulations, might persist under current rules. These lingering incentives could potentially set the stage for bank fragility and future crises. Basel I was amended because of the need to make it more risk sensitive. We show that current Basel rules may also need adjusting to increase their correlation sensitivity in the context of residential mortgages, to reduce the scope of regulatory capital arbitrage opportunities.

[13] Bank of America is the reference bank as it is omitted from the set of bank dummies included in the regression. Hence its correlation coefficient corresponds to the coefficient of ρ, which is negative and equal to -0.9464.

[14] While Wells Fargo's coefficient is positive, when added to the coefficient of the non-interacted correlation variable it turns negative.

The heterogeneous pricing of correlation leads us to examine whether consumers have an economically meaningful advantage in “shopping around”. To investigate this, we employ a stylized example and select a reference mortgage as the basis for calculating the varying impact of correlation on the total interest paid by borrowers to different banks. The reference loan is a 30-year fixed-rate mortgage with an original balance of \$300,000 and a mortgage rate of 5.5%. We determine the difference in interest paid on the reference mortgage by customers of different banks. This is done by considering how banks reflect correlation on their excess mortgage interest rate for different combinations of mortgage characteristics (credit score, loan to value, debt to income, geographic regions and so on). The resulting excess rates are then added to the baseline rate of 5.5% and total interest payments are computed. Figure 3.7 reports the distribution of maximum differences, across banks, in total interest paid on the reference mortgage for each combination of mortgage characteristics. The median (mean) value of the distribution is \$12,064 (\$13,688). Considering that the total interests paid by the borrower is approximately \$310,000, this variation can help borrowers that select the bank with the most negative correlation premium save up to 3.87% (4.42%) of the entire interest amount. The standard deviation of the distribution is also substantial at 7.27%.

3.5 Conclusions

This paper investigates the variability of residential mortgages correlation across mortgage characteristics and the heterogeneous pricing of correlation by top U.S. banks. Through the use of a comprehensive sample of Freddie Mac mortgages that spans 20 years including the GFC, we provide evidence that correlation variability is significantly influenced by mortgage attributes, particularly loan balance and a borrower’s debt-to-income ratio. Risk managers and regulators should account for such variability that may lead to markedly different portfolio risk profiles, particularly in a crisis period. Moreover, we investigate the potential consequences of regulators’ conservative 15% correlation requirement, which may inadvertently incentivise banks to favour high-correlation, high-risk mortgage portfolios and ultimately contribute to greater fragility in the financial system.

We also explore how lending institutions price correlation into mortgage rates. We find that the Global Systemically Important Banks within our sample tend to price correlation negatively. This finding is particularly important, as it points out that current regulation may generate the incentive for banks to increase portfolio correlation (and risk) in order to make a more efficient use of their equity capital. Such negative premium may be the result of the intense market competition that pushes mortgage rates down and disconnects lenders from portfolio concentration consideration. Finally, we employ a stylised example to show how the heterogeneous pricing of correlation risk may lead to substantial gains for those borrowers who shop around.

Figure 3.1: Mortgage Distribution by State

The Graph displays the distribution of mortgages by States across the entire sample. The sample covers Single-Family residential mortgages originated from 1999 to 2017 and securitised by Freddie Mac. The figure displays all mortgages made available in Freddie Mac database.

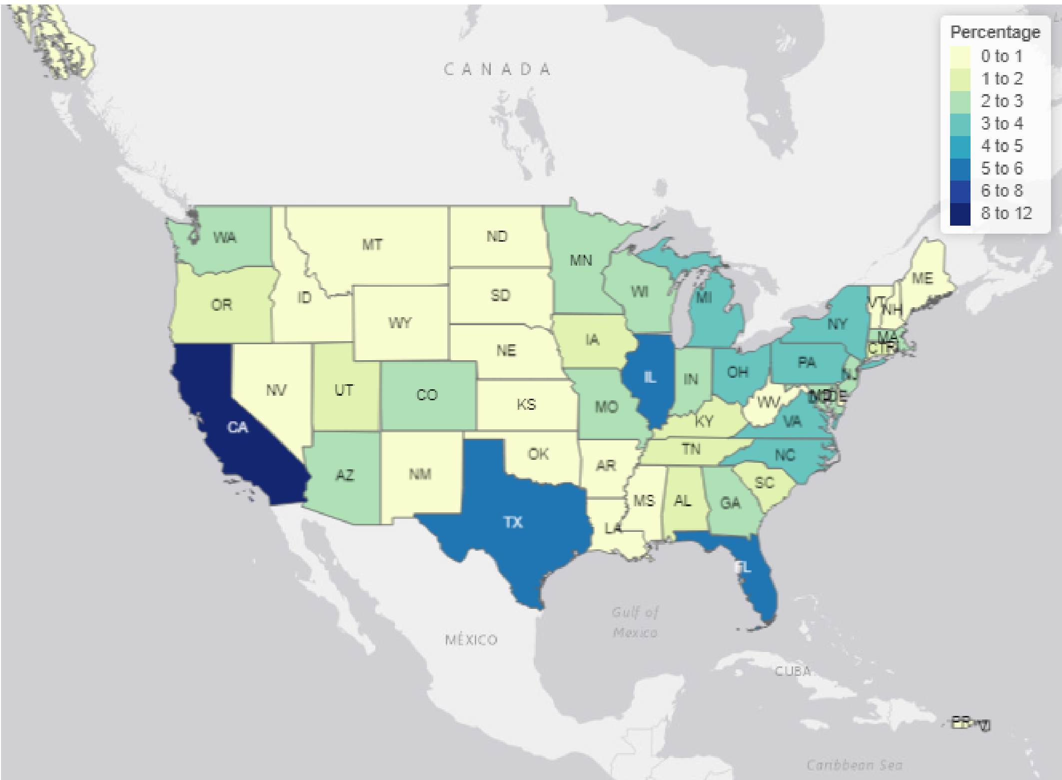


Figure 3.2: Mortgage Defaults over Time

The Graph displays the number of first default occurrences by month, from February 1999 to June 2018 (primary y-axis). The secondary y-axis displays the ratio between first default occurrences and outstanding mortgages by month, from February 1999 to June 2018.

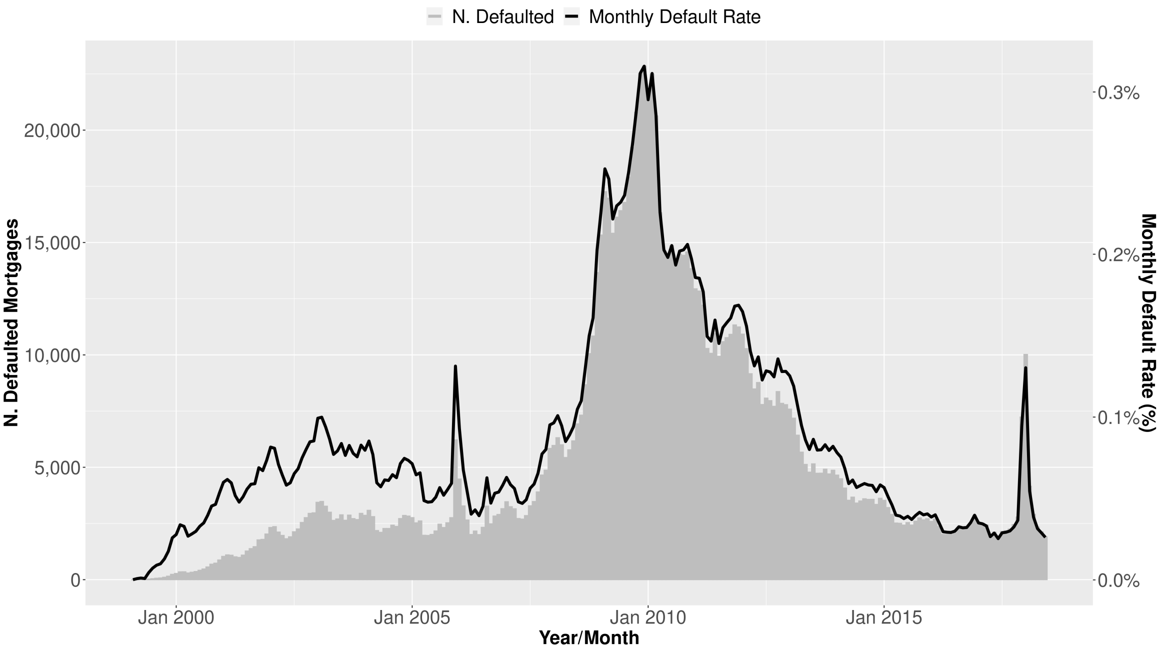


Figure 3.3: Mortgage Origination and Default by Year/Quarter of Origination

The Graph displays a barplot of number of mortgages by year and quarter of origination (primary y-axis). The dark line on the secondary y-axis displays the ratio between first default occurrences and originated mortgages by quarter, from 1999q1 to 2017q4.

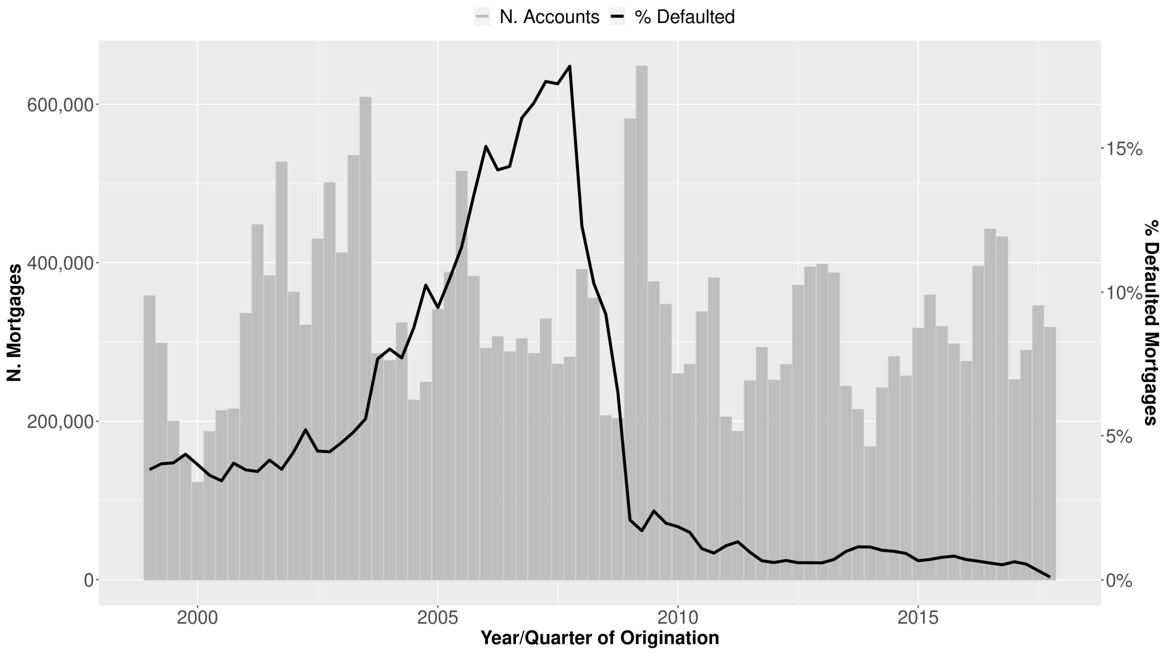


Figure 3.4: Crisis to Pre-crisis Default Rate Ratios by State

The Graph displays the ratio between average yearly default rate during Great Financial Crisis (GFC) and average yearly default rate before the GFC by State across the entire sample.

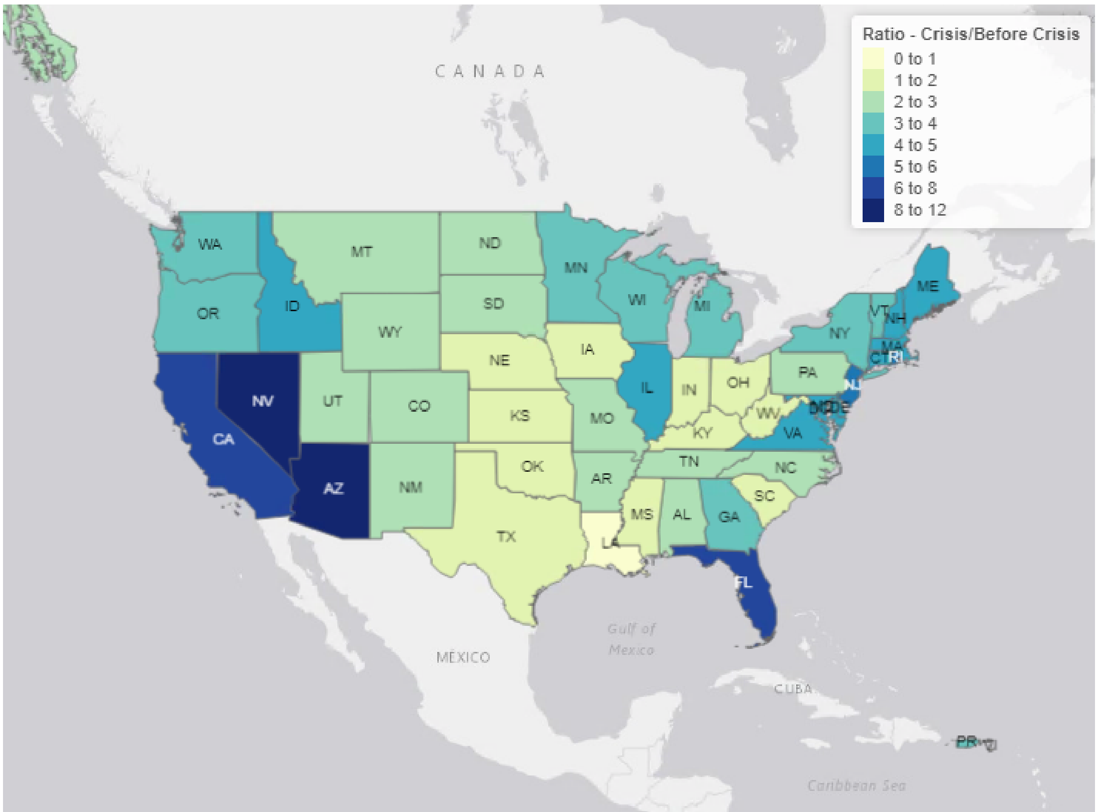
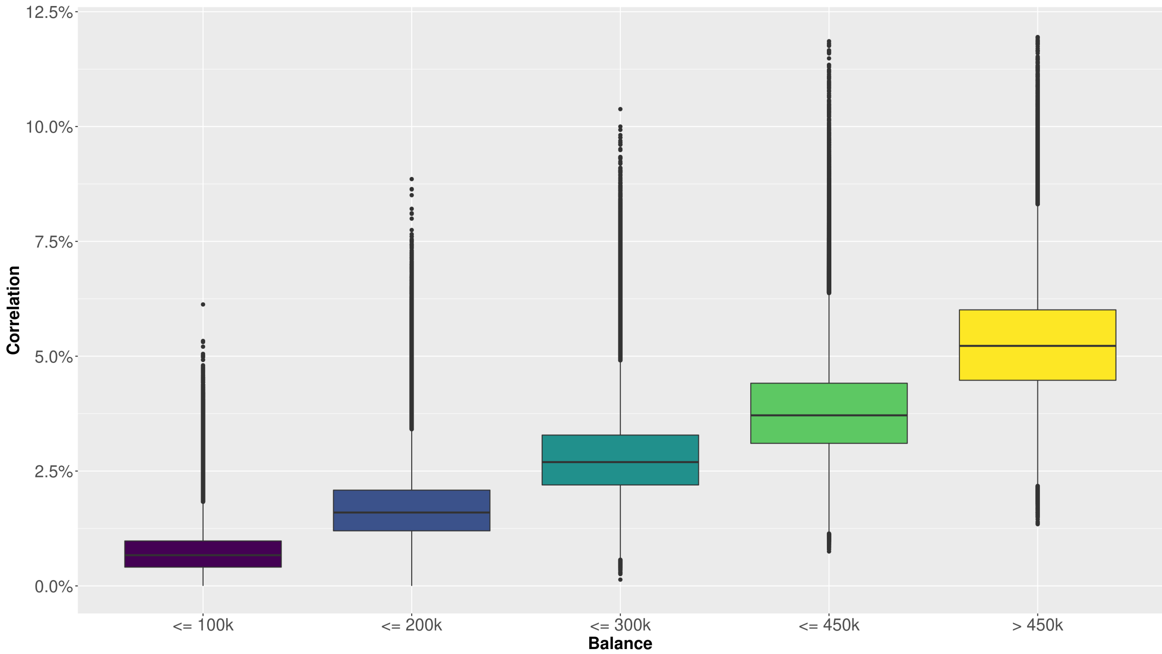
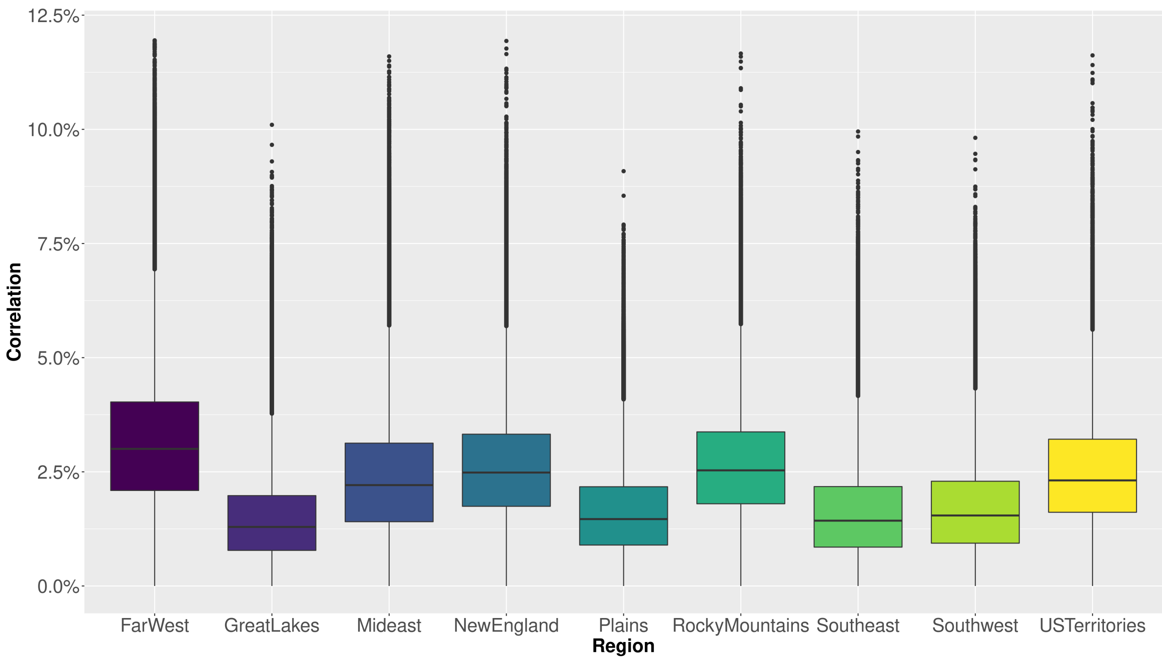


Figure 3.5: Implied Correlation by Balance and Region

The Graph displays the distributions of implied correlations across Balance (a) and Regions (b). The Regions are US state groupings produced by the US Bureau of Economic Analysis (BEA). The implied correlations are derived from crisis period default rates and long run default rates with Equation 3.1 to 3.3. The boxes delimit the 25^{th} and 75^{th} percentiles of the distribution.



(a)



(b)

Figure 3.6: Implied Correlation in Recourse and Non-recourse States

This Graph displays the distributions of implied mortgage correlations in Recourse and Non-Recourse States. The implied correlations are derived from crisis period default rates and long run default rates with Equations 3.1 to 3.3. The boxes delimit the 25^{th} and 75^{th} percentiles of the distribution.

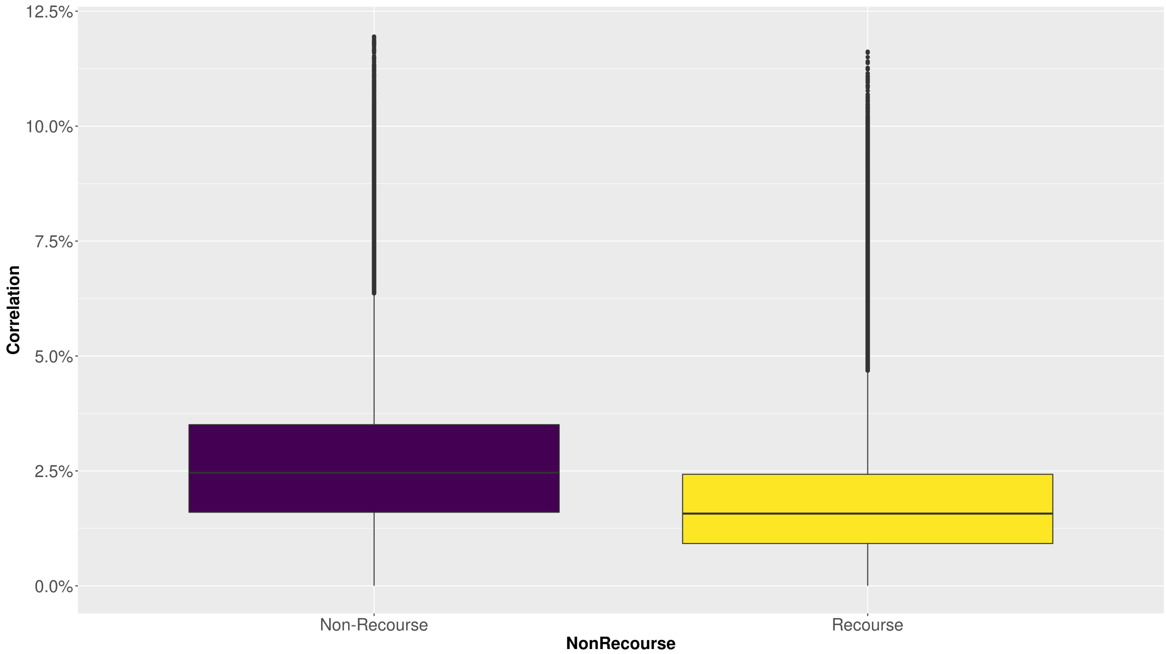


Figure 3.7: Correlation Induced Differentials in Mortgage Interest Payments

The Graph shows the maximum difference among banks in pricing the effect of mortgage correlation. The reference loan is a 30-Year Fixed-Rate Mortgage with original balance of \$ 300,000 and 30-year Fixed-rate of 5.5%. The total interests paid for such mortgage are \$ 310,000. The isolated impact of correlation on Excess Interest rate is first calculated for each Bank. Then the maximum difference amongst banks is produced and plotted. There is no other contributing factor to the difference in total interests paid. The distribution has a mean value of \$ 13,688 (4.41% of total interests) and a median value of \$ 12,064 (3.89% of total interests).

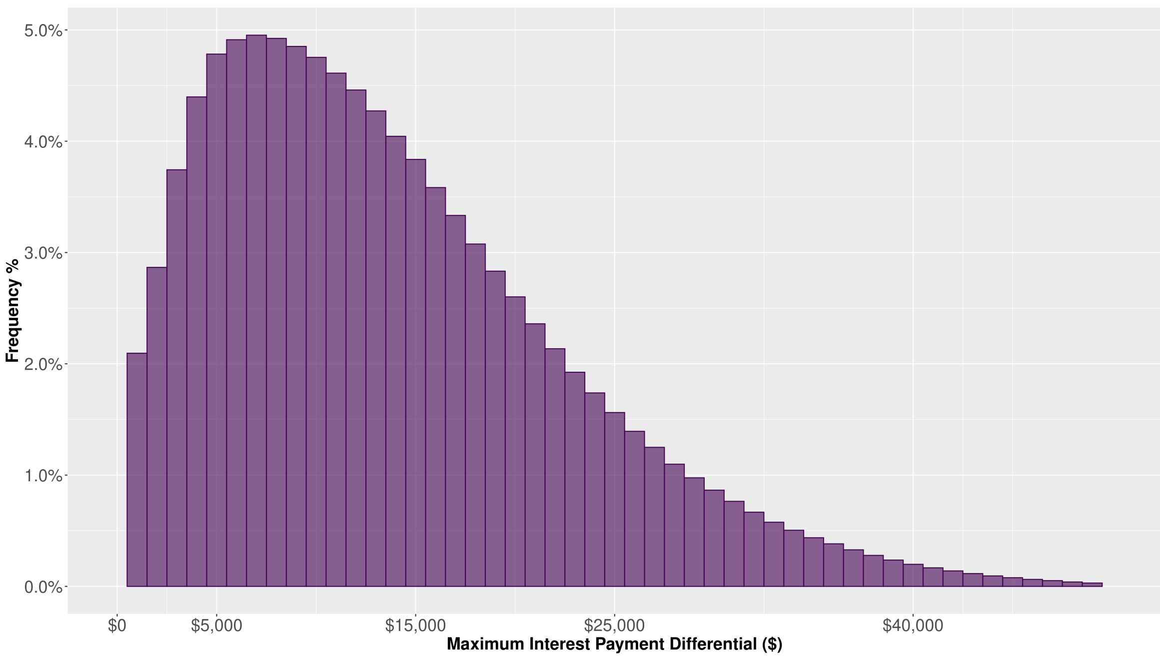


Figure 3.8: Correlation Induced Differentials in Mortgage Interest Payments by Region

The Graph shows the maximum difference amongst banks in pricing the effect of mortgage correlation, breaking down by Bureau of Economic Analysis (BEA) territories. The reference mortgage is a 30-Year Fixed-Rate Mortgage with original balance of \$ 300,000 and 30-year Fixed-rate of 5.5%. The isolated impact of correlation on Excess Interest rate is first calculated for each Bank; then the maximum difference amongst banks is produced and plotted. There is no other contributing factor to the difference in total interests paid.

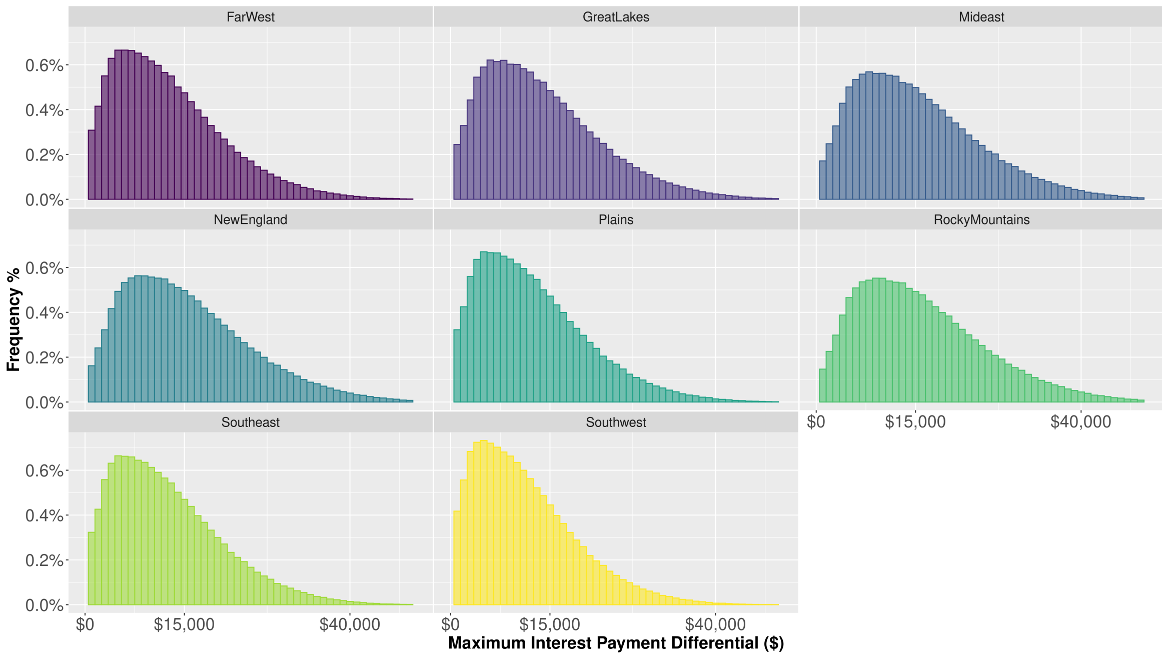


Figure 3.9: Correlation Induced Differentials in Mortgage Interest Payments by Debt-to-Income

The Graph shows the maximum difference amongst banks in pricing the effect of mortgage correlation, by breaking down by *Debt-to-Income* at origination. The reference mortgage is a 30-Year Fixed-Rate Mortgage with original balance of $300,000 and 30-year Fixed-rate of 5.5%. The isolated impact of correlation on Excess Interest rate is first calculated for each Bank; then the maximum difference amongst banks is produced and plotted. There is no other contributing factor to the difference in total interests paid.

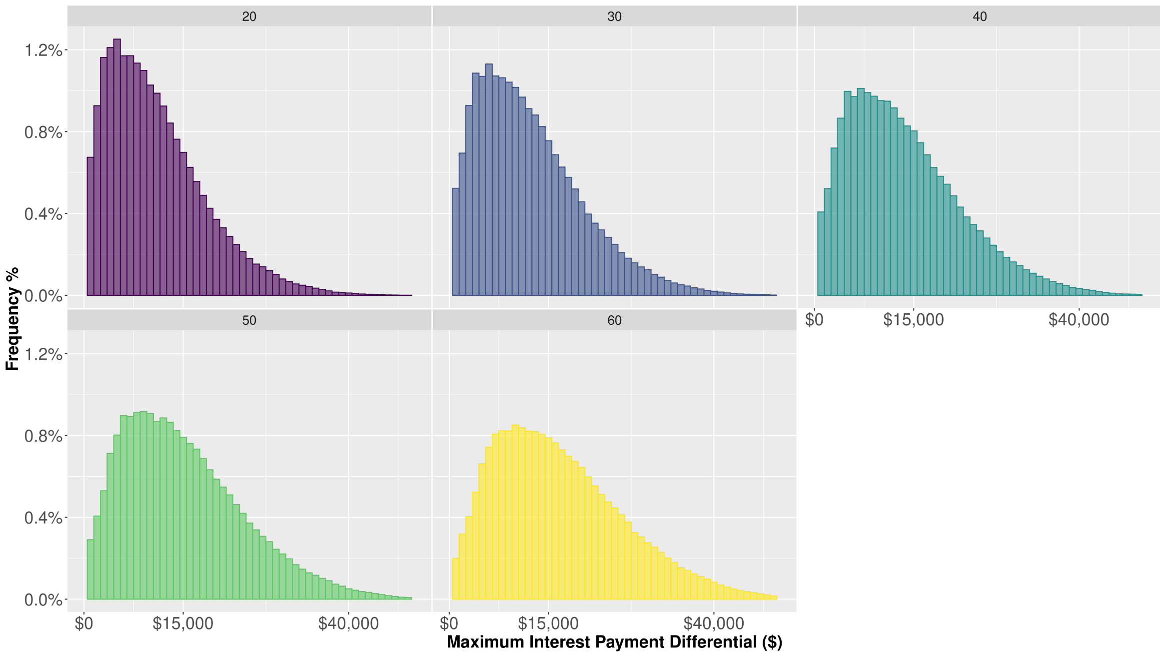


Table 3.1: Mortgage Sample Characteristics at Origination

The Table reports number of accounts, 5^{th} quantile, mean, standard deviation and 95^{th} quantile of *Credit Score*, *Loan-to-Value*, *Debt-to-Income*, *Interest rate* and *Balance* by year of origination. *Credit Score* is borrower's Credit Score at origination. *Loan-to-Value* is the ratio between outstanding *Balance* and $PropertyPrice$ at time of origination. *Debt-to-Income* is the sum of borrower's monthly debt payments, including housing expenses that incorporate mortgage payment, divided by total monthly income used for underwriting. *Interest rate* is the contractual interest rate at origination. *Balance* is the underwritten mortgage outstanding balance.

		Credit Score				Loan-To-Value				Debt-to-Income				Interest Rate				Balance			
Year	No.of Mortgages	q5	Mean	Sd	q95	q5	Mean	Sd	q95	q5	Mean	Sd	q95	q5	Mean	Sd	q95	q5	Mean	Sd	q95
1999	1,095,011	621	711.8	52.0	785	45	76.7	15.2	95	15	32.8	11.0	51	6.5	7.3	0.6	8.3	50,000	125,942	54,599	230,000
2000	786,275	615	712.2	55.6	789	45	77.6	15.5	95	17	34.7	10.7	51	7.4	8.2	0.5	9.0	50,000	131,824	58,840	245,000
2001	1,755,390	617	714.1	58.7	791	45	75.4	14.7	95	15	33.2	11.0	50	6.4	7.0	0.4	7.8	58,000	147,801	64,408	273,000
2002	1,682,997	617	717.1	56.7	792	42	73.9	15.5	95	15	33.5	11.7	53	5.9	6.6	0.5	7.4	59,000	155,506	70,407	292,000
2003	1,927,050	632	724.9	51.6	794	40	72.1	15.7	95	12	32.3	12.3	53	5.1	5.8	0.4	6.5	62,000	161,475	74,414	302,000
2004	1,127,674	624	717.9	54.5	794	42	73.7	15.3	95	15	35.0	12.0	55	5.4	5.9	0.4	6.5	61,000	166,776	78,238	320,000
2005	1,690,993	626	724.4	58.3	802	34	69.6	17.4	95	15	35.3	12.3	56	5.3	5.8	0.4	6.5	57,000	171,054	86,077	343,000
2006	1,260,783	623	723.0	58.3	803	34	70.6	17.4	95	16	36.6	12.2	57	5.8	6.4	0.4	7.0	59,000	179,703	94,317	372,000
2007	1,220,654	621	722.9	58.4	804	35	72.0	17.7	95	16	36.8	12.5	58	5.8	6.4	0.4	7.1	59,000	183,435	98,207	388,000
2008	1,179,578	643	739.7	51.9	806	35	70.1	17.5	95	16	36.4	12.8	58	5.3	6.0	0.5	6.9	62,000	203,644	108,433	417,000
2009	1,974,690	685	762.4	39.6	809	32	65.2	17.0	88	14	31.6	11.6	52	4.4	4.9	0.4	5.6	68,000	214,357	117,130	417,000
2010	1,271,397	684	763.7	40.2	811	33	66.2	17.0	90	14	31.5	10.5	48	3.8	4.6	0.5	5.4	65,000	208,668	120,259	417,000
2011	955,418	685	764.2	39.8	811	33	67.3	17.2	90	15	31.7	10.1	47	3.4	4.3	0.6	5.3	65,000	217,863	125,849	417,000
2012	1,331,301	690	766.5	38.4	812	34	68.0	17.2	95	14	30.8	10.0	46	2.9	3.6	0.4	4.3	70,000	222,291	122,763	417,000
2013	1,300,286	681	759.5	41.0	810	36	70.6	17.2	95	15	32.0	9.8	46	2.8	3.7	0.6	4.8	68,000	218,019	118,454	417,000
2014	975,881	670	751.5	44.1	808	41	75.1	16.2	95	17	33.8	9.2	46	3.4	4.3	0.5	4.9	68,000	219,279	118,550	417,000
2015	1,316,566	670	752.3	44.0	809	40	73.6	16.5	95	17	33.8	9.4	47	3.1	4.0	0.5	4.6	75,000	229,030	119,353	417,000
2016	1,558,394	668	751.1	44.6	809	39	73.0	16.6	95	17	34.1	9.4	48	2.9	3.8	0.5	4.5	80,000	241,231	119,284	431,000
2017	1,217,105	662	747.0	45.9	808	40	74.1	16.5	95	18	35.0	9.4	48	3.4	4.2	0.4	4.9	75,000	235,267	120,715	424,000

Table 3.2: Mortgage Sample Characteristics at Origination: Further Summary Statistics

The Table reports percentage distribution by year of property and borrower types at origination: *First time home buyer*; *Occupancy*: Investment (I), Primary Home(P), Second Home (S); Origination *Channel*: Broker (B), Correspondent (C), Retail (R), TPO Not Specified (T); *Property Type*: Condominium (CO), Co-op (CP), Manufactured Housing (MH), Planned Unit Development (PU), Single-Family (SF); *Purpose*: Cash-out Refinance (C), No Cash-out Refinance (N), Purchase (P); *Number of Borrowers*: Single (S), Joint (J).

		1^{st}Homebuyer		Occupancy			Channel				Property					Purpose			N.Borrowers	
Year	No.of Mortgages	No	Yes	I	P	S	B	C	R	T	CO	CP	MH	PU	SF	C	N	P	1	2
1999	1,095,011	91.72	8.28	3.87	93.01	3.12	0.04	0.1	47.42	52.44	6.79	0.09	0.29	10.46	82.37	17.16	25.91	56.93	36.42	63.51
2000	786,275	82.16	17.84	4.98	90.92	4.10	0.05	0.03	49.02	50.91	8.31	0.13	0.45	12.99	78.11	11.24	13.41	75.34	39.54	60.41
2001	1,755,390	91.28	8.72	4.31	92.66	3.03	0.02	0.01	42.99	56.99	6.86	0.08	0.38	10.95	81.70	25.3	35.1	39.60	37.21	62.76
2002	1,682,997	92.02	7.98	4.46	92.19	3.35	0.04	0.03	42.97	56.96	6.8	0.11	0.56	10.33	82.20	26.5	37.04	36.46	38.03	61.95
2003	1,927,050	94.17	5.83	3.71	93.04	3.25	0.18	0.15	50.7	48.97	6.68	0.14	0.66	11.62	80.90	24.38	47.03	28.59	37.14	62.83
2004	1,127,674	90.89	9.11	4.34	91.08	4.59	0.09	0.3	44.62	54.99	7.24	0.42	1.07	13.88	77.37	25.39	28.1	46.51	41.74	58.23
2005	1,690,993	91.63	8.37	3.35	91.89	4.76	0.06	0.18	45.82	53.93	6.73	0.33	1.28	12.41	79.25	38.1	22.86	39.04	41.85	58.12
2006	1,260,783	89.35	10.65	4.68	90.08	5.25	0.03	0.05	40.09	59.83	8.12	0.37	1.63	14.44	75.44	36.83	16.33	46.84	44.55	55.41
2007	1,220,654	88.54	11.46	7.23	87.81	4.95	0.06	0.07	41.5	58.37	8.4	0.37	1.34	13.98	75.92	37.02	19.15	43.83	46.86	53.09
2008	1,179,578	89.85	10.15	7.82	86.92	5.26	10.19	16.95	45.73	27.12	7.99	0.39	0.58	16.48	74.55	33.45	28.27	38.29	46.52	53.43
2009	1,974,690	93.27	6.73	3.1	92.38	4.52	17.64	27.73	54.62	0.00	5.48	0.26	0.23	19.75	74.28	31.44	46.98	21.57	37.9	62.09
2010	1,271,397	91.13	8.87	4.98	90.54	4.48	11.46	38.79	49.74	0.00	5.24	0.21	0.24	19.64	74.67	31.1	41.29	27.62	38.19	61.81
2011	955,418	90.86	9.14	5.84	89.54	4.62	11.16	40.85	48	0.00	4.92	0.15	0.26	21.25	73.41	26.78	41.72	31.50	38.49	61.51
2012	1,331,301	92.33	7.67	5.25	90.76	3.99	10.14	37.34	52.52	0.00	4.52	0.11	0.27	22.47	72.62	23.21	50.56	26.23	37.92	62.08
2013	1,300,286	87.61	12.39	7.06	88.81	4.13	8.76	35.45	55.79	0.00	6.33	0.23	0.26	25.08	68.10	23.1	38.45	38.45	43.04	56.96
2014	975,881	79.97	20.03	7.88	88.13	3.99	9.92	34.46	55.62	0.00	7.47	0.17	0.3	27.19	64.87	20.12	20.91	58.97	48.19	51.81
2015	1,316,566	83.6	16.40	7.57	88.77	3.66	10.67	30.9	58.43	0.00	7.82	0.19	0.28	27.2	64.51	22.86	29.17	47.97	48.22	51.78
2016	1,558,394	84.84	15.16	7.77	88.84	3.39	10.06	31.39	58.55	0.00	8.11	0.16	0.27	27.57	63.89	24.42	30.57	45.01	49.42	50.58
2017	1,217,105	81.5	18.50	9.95	86.01	4.04	9.73	33.53	56.74	0.00	7.97	0.14	0.42	27.62	63.85	25.36	17.39	57.24	50.58	49.42

Table 3.3: Yearly Default Rate by Credit Score, Debt-to-Income and Excess Interest Rate

The Table reports the yearly default rate (expressed in percentage) by year of observation. Yearly default rate, number of observations and number of defaults at portfolio level are reported in the first three columns. Yearly default rate is the ratio of defaulted mortgages over the number of outstanding active mortgages in year t. The yearly default rate is then segmented by *Credit Score*, *Debt-to-Income* and *Excess Interest Rate* by different buckets. *Credit Score* is borrower's Credit Score at origination. *Debt-to-Income* is the sum of borrower's monthly debt payments, including housing expenses that incorporate mortgage payment, divided by total monthly income used for underwriting. *Excess Interest Rate* is the difference between rate at origination and average interest rate of all mortgages generated in the same quarter.

				Credit Score					Debt-to-Income				Excess IR					
Year	No.of Mortgages	Defaults	All	⩽579	580-669	670-739	740-799	≥800	⩽20%	20%-40%	40%-55%	≥55%	⩽-1%	-1%–0.5%	-0.5%-0%	0%-0.5%	0.5%-1%	≥1%
1999	939,197	718	0.08	1.04	0.17	0.05	0.02	0.02	0.07	0.08	0.08	0.11	0.03	0.03	0.05	0.09	0.21	0.36
2000	1,706,123	5,729	0.34	2.12	0.89	0.22	0.07	0.07	0.22	0.33	0.41	0.49	0.13	0.1	0.22	0.38	0.84	1.47
2001	3,292,855	16,049	0.49	2.67	1.35	0.33	0.09	0.10	0.27	0.47	0.64	0.69	0.15	0.18	0.31	0.52	1.31	3.2
2002	4,382,304	28,120	0.64	3.79	1.81	0.44	0.11	0.09	0.37	0.6	0.89	0.66	0.32	0.29	0.36	0.65	2.04	5.82
2003	5,311,191	35,279	0.66	4.68	2.03	0.47	0.11	0.08	0.36	0.63	0.95	0.66	0.38	0.26	0.39	0.75	1.73	5.66
2004	4,631,059	30,804	0.67	4.32	1.91	0.53	0.12	0.09	0.34	0.65	0.91	0.66	0.45	0.26	0.41	0.77	1.51	4.64
2005	5,424,031	32,325	0.60	3.48	1.73	0.52	0.14	0.07	0.35	0.59	0.77	0.60	0.27	0.27	0.42	0.65	1.44	4
2006	5,927,775	33,570	0.57	3.01	1.61	0.52	0.16	0.09	0.35	0.55	0.71	0.59	0.26	0.27	0.41	0.63	1.32	3.47
2007	6,641,321	44,175	0.67	3.61	1.93	0.64	0.16	0.08	0.35	0.63	0.87	0.81	0.26	0.26	0.44	0.8	1.58	3.23
2008	7,359,285	93,166	1.27	5.76	3.63	1.35	0.37	0.17	0.59	1.11	1.78	1.87	0.3	0.44	0.82	1.59	3.02	5.12
2009	8,645,786	217,599	2.52	10.34	7.74	3.22	0.86	0.30	0.89	2.05	3.86	5.11	0.79	1.12	1.79	3.1	5.29	8.23
2010	8,370,112	195,879	2.34	8.38	7.04	3.24	0.98	0.34	0.8	1.88	3.62	5.87	1.12	1.14	1.87	2.74	4.34	6.41
2011	7,803,125	134,082	1.72	6.36	5.14	2.47	0.81	0.31	0.66	1.42	2.57	4.73	0.92	0.82	1.46	1.95	2.66	4.7
2012	7,776,197	103,176	1.33	5.13	4.31	2.03	0.64	0.26	0.53	1.11	2	3.85	0.76	0.58	1.22	1.45	1.98	3.38
2013	7,245,881	65,902	0.91	4.39	3.45	1.4	0.42	0.17	0.39	0.77	1.35	3.16	0.43	0.34	0.87	0.97	1.4	2.5
2014	6,844,299	45,048	0.66	3.96	2.72	1.01	0.3	0.13	0.33	0.56	0.94	2.63	0.23	0.25	0.65	0.68	1.06	2
2015	7,515,347	32,781	0.44	3.1	1.86	0.68	0.21	0.10	0.24	0.37	0.61	2.07	0.15	0.17	0.41	0.46	0.75	1.45
2016	8,128,933	27,950	0.34	2.86	1.5	0.54	0.16	0.08	0.2	0.3	0.46	1.57	0.12	0.13	0.28	0.38	0.66	1.2
2017	8,415,102	32,457	0.39	3.57	1.65	0.61	0.18	0.09	0.2	0.34	0.54	1.69	0.14	0.15	0.29	0.43	0.79	1.23
2018	7,705,902	23,463	0.30	2.08	1.15	0.5	0.16	0.07	0.13	0.26	0.46	1.10	0.21	0.14	0.21	0.34	0.65	0.97

Table 3.4: Yearly Default Rate by Loan-to-Value

The Table reports yearly default rate (expressed in percentage) by year of observation. Number of active mortgages, number of defaults and default rates by year are reported in the first three columns. The annual default rate is segmented by loan-to-value at origination and updated loan-to-value. Loan-to-value at origination is the ratio between the loan's outstanding balance and the property price at the time of origination. Updated loan-to-value is the ratio between the mortgage outstanding balance and the current property price derived from the relevant state-level House Price Index.

				Original Loan-to-Value						Updated Loan-to-Value					
Year	No.of Mortgages	No.of Defaults	All	$\leqslant$30%	30%-50%	50%-70%	70%-80%	80%-90%	$\geq$ 90%	$\leqslant$30%	30%-50%	50%-70%	70%-80%	80%-90%	$\geq$ 90%
1999	939,197	718	0.08	0.0415	0.028	0.0438	0.0662	0.1275	0.11	0.0428	0.0265	0.0433	0.0692	0.1215	0.1186
2000	1,706,123	5,729	0.34	0.1023	0.1166	0.1712	0.271	0.5195	0.59	0.0958	0.1141	0.1889	0.3101	0.5859	0.6528
2001	3,292,855	16,049	0.49	0.1805	0.1535	0.2447	0.3661	0.8163	0.99	0.1901	0.1692	0.3632	0.419	1.0033	0.7113
2002	4,382,304	28,120	0.64	0.1322	0.1581	0.2839	0.4807	1.2205	1.46	0.1523	0.1824	0.43	0.6688	1.5213	1.6083
2003	5,311,191	35,279	0.66	0.1421	0.1394	0.2877	0.5155	1.3344	1.72	0.1994	0.2168	0.5125	0.726	1.556	1.236
2004	4,631,059	30,804	0.67	0.1023	0.1446	0.2635	0.5148	1.4233	1.83	0.1356	0.2545	0.5508	0.8067	1.8769	1.3792
2005	5,424,031	32,325	0.60	0.1188	0.1397	0.2851	0.4989	1.3462	1.69	0.1351	0.2822	0.6497	0.7492	1.4613	0.6996
2006	5,927,775	33,570	0.57	0.1264	0.1789	0.3323	0.5027	1.2308	1.52	0.1703	0.3212	0.6297	0.6412	1.0125	0.9294
2007	6,641,321	44,175	0.67	0.1654	0.2243	0.4352	0.623	1.3135	1.61	0.1862	0.3311	0.6584	0.8127	0.8862	1.3502
2008	7,359,285	93,166	1.27	0.2332	0.3802	0.8423	1.2563	2.334	2.95	0.2345	0.4873	0.8905	1.2707	1.5065	2.1287
2009	8,645,786	217,599	2.52	0.3254	0.6484	1.8049	2.7316	4.7452	5.53	0.2199	0.454	1.0165	1.4708	2.7914	7.5737
2010	8,370,112	195,879	2.34	0.3499	0.6862	1.7586	2.5861	4.3412	5.00	0.2368	0.5082	1.0691	1.5581	3.1207	7.8126
2011	7,803,125	134,082	1.72	0.2973	0.5599	1.2999	1.9232	3.1203	3.56	0.2038	0.4295	0.8787	1.1549	1.9976	5.3259
2012	7,776,197	103,176	1.33	0.255	0.4648	1.0072	1.4891	2.3772	2.64	0.1824	0.3821	0.7171	1.0767	2.4538	6.2198
2013	7,245,881	65,902	0.91	0.218	0.3638	0.7275	1.0062	1.5767	1.55	0.1799	0.422	0.742	1.1266	2.0439	4.2464
2014	6,844,299	45,048	0.66	0.2135	0.3115	0.5549	0.7166	1.0729	0.93	0.189	0.42	0.6908	0.8729	1.2738	1.7796
2015	7,515,347	32,781	0.44	0.1717	0.2389	0.3844	0.461	0.6452	0.60	0.1803	0.3639	0.5262	0.4662	0.5984	0.5479
2016	8,128,933	27,950	0.34	0.1521	0.2002	0.2963	0.359	0.4845	0.48	0.1707	0.3316	0.421	0.3328	0.3828	0.3267
2017	8,415,102	32,457	0.39	0.1594	0.2231	0.3269	0.3916	0.5248	0.60	0.2068	0.3843	0.4411	0.3961	0.5228	0.389
2018	7,705,902	23,463	0.30	0.1299	0.1791	0.2514	0.3077	0.3949	0.50	0.1508	0.2612	0.3303	0.4135	0.5362	0.9217

Table 3.5: Yearly Default Rate by Type of Property and Borrower

The table reports yearly default rate (expressed in percentage) by year of observation. The annual default rate is segmented by *first time home buyer*; *Occupancy*: Investment (I), Primary (P), Second Home (S); *Origination Channel*: Broker (B), Correspondent (C), Retail (R), TPO Not Specified (T); *Property Type*: Condominium (CO), Co-op (CP), Manufactured Housing (MH), Planned Unit Development (PU), Single-Family (SF); *Purpose*: Cash-out Refinance (C), No Cash-out Refinance (N), Purchase (P); *Number of Borrowers*: Single (S), Joint (J).

		1^{st} Time Buyer		Occupancy			Channel				Property					Purpose		
Year	All	No	Yes	I	P	S	B	C	R	T	CO	CP	MH	PU	SF	C	N	P
1999	0.08	0.0748	0.09	0.1268	0.0747	0.07	0	0.1548	0.0678	0.08	0.0656	0.1383	0.1124	0.0499	0.08	0.0699	0.102	0.0662
2000	0.34	0.3349	0.34	0.2996	0.3422	0.21	0.2016	0.6006	0.2557	0.41	0.2405	0.1156	1.0604	0.207	0.36	0.4077	0.4533	0.2819
2001	0.49	0.4772	0.56	0.5565	0.4916	0.28	1.4388	0.8706	0.3893	0.57	0.3217	0.0994	2.0832	0.3237	0.52	0.4678	0.5139	0.4814
2002	0.64	0.6311	0.73	0.9713	0.6371	0.33	2.0496	0.9943	0.4524	0.79	0.4293	0.3266	2.3181	0.4218	0.68	0.5649	0.6633	0.6656
2003	0.66	0.6476	0.84	1.0695	0.6562	0.35	1.1952	1.5873	0.4455	0.86	0.3598	0.1896	2.0569	0.408	0.71	0.6136	0.6197	0.7436
2004	0.67	0.6442	0.91	0.8106	0.6718	0.31	0.7273	2.5641	0.4763	0.84	0.3601	0.1305	2.1229	0.3707	0.72	0.6359	0.6355	0.7158
2005	0.60	0.5869	0.70	0.7328	0.6034	0.28	1.6908	1.9231	0.4369	0.74	0.3187	0.1544	1.5665	0.292	0.65	0.5401	0.6478	0.5906
2006	0.57	0.5565	0.67	0.6344	0.5654	0.52	1.4925	1.2195	0.4605	0.66	0.57	0.1756	1.15	0.3274	0.60	0.5337	0.6242	0.5468
2007	0.67	0.656	0.76	0.6003	0.6814	0.40	1.0274	0.6803	0.5316	0.78	0.5147	0.2567	1.2593	0.4447	0.71	0.7255	0.6843	0.6047
2008	1.27	1.25	1.42	1.3962	1.27	1.05	0.2547	0.0945	0.971	1.61	1.2845	0.4069	2.0553	1.127	1.28	1.4852	1.1131	1.1983
2009	2.52	2.4963	2.73	3.0695	2.5183	1.93	0.9771	0.5657	1.8519	3.95	2.7131	0.7879	3.8923	2.3078	2.53	3.2673	1.8847	2.4245
2010	2.34	2.3153	2.60	2.6351	2.3554	1.74	1.0891	0.5602	1.7989	4.20	2.701	0.7313	4.0692	2.0779	2.35	3.0194	1.6717	2.374
2011	1.72	1.7008	1.90	2.0052	1.7188	1.38	0.7759	0.5164	1.3706	3.45	2.1338	0.7136	3.1225	1.4511	1.72	2.1903	1.2011	1.8185
2012	1.33	1.3054	1.55	1.4061	1.3357	1.08	0.5999	0.3763	1.0962	3.15	1.7693	0.838	2.7906	0.9972	1.35	1.7434	0.8827	1.4563
2013	0.91	0.8993	1.01	0.8923	0.9221	0.70	0.47	0.3032	0.7576	2.63	1.085	0.8984	2.1207	0.5523	0.97	1.2452	0.6261	0.9423
2014	0.66	0.6587	0.65	0.5978	0.6725	0.47	0.368	0.2736	0.561	2.31	0.6925	0.6947	1.7062	0.3342	0.73	0.9314	0.4895	0.6179
2015	0.44	0.4364	0.43	0.3906	0.4452	0.32	0.2607	0.2306	0.3698	1.80	0.441	0.5357	1.2892	0.2176	0.49	0.6162	0.3311	0.4069
2016	0.34	0.3386	0.38	0.305	0.351	0.26	0.2353	0.2203	0.2956	1.55	0.3162	0.3887	1.1024	0.1943	0.39	0.4597	0.2613	0.339
2017	0.39	0.3716	0.47	0.3095	0.3986	0.25	0.3466	0.3065	0.3343	1.57	0.3263	0.375	0.9339	0.3414	0.40	0.4847	0.2862	0.4004
2018	0.30	0.2875	0.41	0.2334	0.3143	0.22	0.3474	0.2405	0.2907	0.85	0.2963	0.2382	0.4864	0.3419	0.29	0.3832	0.1988	0.3363

Table 3.6: HMDA Representativeness

The Table shows the breakdown of mortgage applications and originations across the United States with a focus on conventional loans issued by Fannie Mae (FNMA) and Freddie Mac (FHLMC). The source is the HMDA (Home Mortgage Disclosure Act) database. The sample period is from 2007 to 2017. The sample used for the analysis in this paper relates to conventional originated mortgages.

Data	Percentage	Volumes
Total Mortgage Applications		187,462,446
Total Mortgages Originated		90,171,323
	% Total Applications	48.1 %
Conventional Originated		62,317,732
	% Total Originated	69.1 %
FHLMC and FNMA Originated		41,550,067
	% Total Originated	46.1 %
FHLMC and FNMA Conventional Originated		40,849,709
	% Total Conventional Originated	65.6 %
FHLMC Conventional Originated		15,976,438
	% Total Conventional Originated	25.6 %
	% Total Originated	17.7 %

Table 3.7: Default Probability: Marginal Effects

The Table shows average marginal effects of explanatory variables on default probability, split by Long Run and Crisis. Standard errors of marginal effects are calculated using the delta method and are reported in parentheses. *Credit Score* is borrower's Credit Score at origination. *Debt-to-Income* is the sum of borrower's monthly debt payments, including housing expenses that incorporate mortgage payment, divided by total monthly income used for underwriting. *Excess Interest Rate* is the difference between rate at origination and average interest rate of all mortgages generated in the same quarter. *Joint* captures loans with more than one borrower. *Balance* is the natural logarithm of mortgage outstanding balance. *Updated LTV* is the ratio between outstanding $Balance_t$ and $PropertyPrice_t$, which is derived from State-level House Price Index at time t. Ump_{12} is the 1-year growth rate of State-level Unemployment. *Loan Age* is the age of the loan in years. *Region* Fixed Effects (FE) includes US Bureau of Economic Static US states grouping; *Non recourse* FE differentiate Non-recourse States from Recourse states; *Bank* FE capture the top lenders in the sample which were observed over the entire observation period; Loan FE include *Loan Purpose* and *Occupancy Status*; Borrower FE include *First Time Homebuyer* flag; Property FE covers *Number of Units* and *Property Type*. The *Crisis* period spans over the years of mortgage downturn (2009, 2010 and 2011) and is activated using a dummy variable. The sample includes mortgages originated from 1999 to 2017 and observed from 1999 to 2018. ***, **, * denote statistical significance at the 1%, 5% and 10% levels respectively.

Variables	Model1	Model2	Model3	Model4	Model5
Credit Score	-0.0001071***	-0.0001089***	-0.0000938***	-0.0000943***	-0.000088***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Debt-to-Income	0.0002853***	0.000259***	0.000183***	0.0001819***	0.000144***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Excess Int. Rate	0.0052216***	0.0054109***	0.0049472***	0.0050559***	0.004585***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Joint	-0.0049071***	-0.0048926***	-0.0051561***	-0.0051478***	-0.0048393***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Balance			0.0006959***	0.0007263***	-0.000777***
			(0.000)	(0.000)	(0.000)
Updated LTV			0.0003088***	0.0002904***	0.000274***
			(0.000)	(0.000)	(0.000)
Ump12			0.0014191***	0.0012435***	0.00119***
			(0.000)	(0.000)	(0.000)
Crisis		0.0154335***		0.002683***	0.0029457***
		(0.000)		(0.000)	(0.000)
Crisis*Credit Score					-0.000106***
					(0.000)
Crisis*Debt-to-Income					0.000227***
					(0.000)
Crisis*Excess Int. Rate					0.006182***
					(0.000)
Crisis*Joint					-0.0058166***
					(0.000)
Crisis*Balance					0.003971***
					(0.000)
Crisis*Updated LTV					0.000326***
					(0.000)
LoanAge	No	No	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes
Non Recourse FE	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes
Loan FE	Yes	Yes	Yes	Yes	Yes
Borrower FE	Yes	Yes	Yes	Yes	Yes
Property FE	Yes	Yes	Yes	Yes	Yes
Observations	122,064,071	122,064,071	122,064,071	122,064,071	122,064,071
AUROC	78.780%	81.580%	87.760%	87.780%	87.970%
GINI	57.560%	63.160%	75.520%	75.560%	75.940%
Pseudo-R2	9.370%	12.410%	19.880%	20.010%	20.480%

Table 3.8: In-Sample Implied Correlations

The Table displays summary statistics for implied correlations calculated for different mortgage characteristics. Correlations are implied from crisis period default probabilities and long run default probabilities by employing Equation 4.3. *Credit Score* is a borrower's credit score at origination. *Updated LTV* is the ratio between the mortgage outstanding balance and the current property price derived from the relevant state-level House Price Index. The *Debt-to-Income* ratio measures how much of a borrower's income goes towards paying off their debts every month. It is calculated by dividing the total monthly debt payments, including the mortgage and other loan repayments, by the total monthly income reported when underwriting the mortgage. *Balance* is a mortgage's outstanding balance. *Region* includes US state groupings produced by the US Bureau of Economic Analysis (BEA); Borrower's liability differentiates between recourse and non-recourse states.

Variable	Segment	N.Observations	Mean	Median	SD	q75	q90	q99	Max
Credit Score	≤ 579	103,166	1.60%	1.33%	1.25%	2.30%	3.33%	5.34%	9.64%
	580-669	2,932,751	1.86%	1.61%	1.31%	2.61%	3.67%	5.81%	13.07%
	670-739	8,155,052	2.10%	1.86%	1.33%	2.87%	3.93%	6.05%	12.60%
	740-799	11,641,717	2.14%	1.93%	1.26%	2.88%	3.87%	5.82%	12.99%
	≥ 800	2,419,57	2.01%	1.80%	1.20%	2.72%	3.67%	5.50%	12.53%
Updated LTV	≤ 40%	1,740,420	1.80%	1.54%	1.24%	2.52%	3.56%	5.45%	10.50%
	41%-60%	4,103,466	2.16%	1.93%	1.32%	2.95%	3.98%	5.96%	12.25%
	61%-70%	3,818,242	2.28%	2.06%	1.35%	3.08%	4.11%	6.20%	12.99%
	71%-85%	10,044,337	2.08%	1.86%	1.25%	2.80%	3.78%	5.79%	12.79%
	86%-99%	4,432,354	1.88%	1.67%	1.20%	2.60%	3.53%	5.36%	13.07%
	≥ 100%	1,113,437	2.32%	2.05%	1.51%	3.22%	4.45%	6.61%	12.53%
Debt-to-Income	≤ 15%	1,370,102	1.39%	1.20%	0.96%	1.92%	2.71%	4.30%	10.54%
	16%-30%	8,606,096	1.76%	1.58%	1.10%	2.41%	3.27%	4.98%	11.31%
	31%-45%	11,746,676	2.24%	2.04%	1.32%	3.04%	4.05%	6.04%	12.60%
	46%-54%	2,904,321	2.54%	2.33%	1.42%	3.41%	4.48%	6.51%	13.07%
	≥ 55%	625,061	2.66%	2.45%	1.48%	2.45%	4.68%	6.86%	12.53%
Balance	≤ 100k	5,191,020	0.73%	0.67%	0.46%	0.98%	1.33%	2.16%	6.13%
	100k-200k	10,684,158	1.69%	1.60%	0.68%	2.08%	2.60%	3.71%	8.86%
	200k-300k	5,704,745	2.80%	2.69%	0.83%	3.28%	3.89%	5.19%	10.38%
	300k-450k	3,197,043	3.82%	3.71%	1.00%	4.41%	5.13%	6.67%	12.33%
	≥ 450k	475,290	5.28%	5.23%	1.18%	6.01%	6.79%	8.40%	13.07%
Region	FarWest	4,776,565	3.13%	3.00%	1.41%	4.03%	5.02%	6.90%	13.07%
	GreatLakes	4,549,138	1.46%	1.29%	0.92%	1.98%	2.74%	4.19%	10.10%
	Mideast	3,105,342	2.35%	2.21%	1.26%	3.13%	4.03%	5.86%	12.01%
	NewEngl.	1,388,126	2.60%	2.48%	1.18%	3.32%	4.16%	5.92%	12.09%
	Plains	2,077,061	1.61%	1.46%	0.95%	2.17%	2.92%	4.30%	9.08%
	RockyMount.	1,338,460	2.65%	2.53%	1.17%	3.37%	4.20%	5.82%	11.66%
	Southeast	5,603,178	1.59%	1.43%	0.98%	2.18%	2.95%	4.41%	9.95%
	Southwest	2,377,482	1.68%	1.54%	1.00%	2.29%	3.06%	4.43%	9.81%
	US Territories	36,904	2.56%	1.36%	2.31%	3.21%	4.32%	7.00%	12.79%
Borrower's liability	Non-Recourse	8,848,243	2.65%	2.46%	1.39%	3.51%	4.55%	6.53%	13.07%
	Recourse	16,404,013	1.77%	1.57%	1.11%	2.43%	3.31%	4.99%	12.79%

Table 3.9: Regulatory Capital Impact

The Table displays regulatory capital using implied correlations for different mortgage characteristics. 5%q and 95%q denote the 5% and 95% quantiles of the correlation ρ distribution within a specific mortgage characteristic (e.g., credit score < 580). To compute regulatory capital we employ a loss given default (LGD) of 10% and a PD equal to the average $PD_{LongRun}$ of the mortgage characteristic considered. Credit Score is a borrower's credit score at origination. Updated LTV is the ratio between the mortgage outstanding balance and the current property price derived from the relevant state-level House Price Index. The Debt-to-Income ratio measures how much of a borrower's income goes towards paying off their debts every month. It is calculated by dividing the total monthly debt payments, including the mortgage and other loan repayments, by the total monthly income reported when underwriting the mortgage. Balance is a mortgage's outstanding balance. Region includes US state groupings produced by the US Bureau of Economic Analysis (BEA); Borrower's liability differentiates between recourse and non-recourse states.

		Regulatory Capital based on:			Distance from required capital:	
Variable	Segment	5%q ρ	95%q ρ	Required ρ 15%	15%-5%q ratio	15%-95%q ratio
Credit Score	$\leq$ 579	0.160%	1.459%	3.579%	22.3	2.5
	580-669	0.119%	0.770%	2.076%	17.5	2.7
	670-739	0.077%	0.422%	1.199%	15.6	2.8
	740-799	0.039%	0.194%	0.615%	16.0	3.2
	$\geq$ 800	0.021%	0.112%	0.389%	18.5	3.5
Updated LTV	$\leq$ 40%	0.009%	0.070%	0.256%	27.4	3.7
	41%-60%	0.028%	0.152%	0.483%	17.5	3.2
	61%-70%	0.050%	0.252%	0.740%	14.9	2.9
	71%-85%	0.065%	0.326%	0.984%	15.0	3.0
	86%-99%	0.085%	0.481%	1.447%	17.0	3.0
	$\geq$ 100%	0.218%	1.194%	2.679%	12.3	2.2
Debt-to-Income	$\leq$ 15%	0.020%	0.136%	0.575%	28.2	4.2
	16%-30%	0.042%	0.225%	0.792%	19.0	3.5
	31%-45%	0.083%	0.404%	1.140%	13.7	2.8
	46%-54%	0.126%	0.558%	1.418%	11.2	2.5
	$\geq$ 55%	0.185%	0.770%	1.815%	9.8	2.4
Balance	$\leq$ 100k	0.038%	0.187%	1.176%	31.0	6.3
	100k-200k	0.108%	0.273%	1.109%	10.3	4.1
	200k-300k	0.155%	0.321%	0.992%	6.4	3.1
	300k-450k	0.174%	0.345%	0.870%	5.0	2.5
	$\geq$ 450k	0.154%	0.295%	0.610%	4.0	2.1
Region	FarWest	0.106%	0.368%	0.916%	8.7	2.5
	GreatLakes	0.057%	0.288%	1.098%	19.2	3.8
	Mideast	0.074%	0.328%	0.962%	13.0	2.9
	NewEngl.	0.088%	0.296%	0.867%	9.9	2.9
	Plains	0.052%	0.253%	0.949%	18.3	3.8
	RockyMount.	0.096%	0.315%	0.912%	9.5	2.9
	Southeast	0.072%	0.359%	1.270%	17.7	3.5
	Southwest	0.063%	0.321%	1.138%	18.1	3.5
	USTerr.	0.192%	0.674%	1.664%	8.7	2.5
Borrower's liability	Non-Recourse	0.088%	0.365%	0.968%	11.0	2.7
	Recourse	0.063%	0.335%	1.109%	17.6	3.3
Average		0.091%	0.401%	1.150%	15.1	3.1

Table 3.10: Determinants of Excess Mortgage Interest Rates

The Table reports OLS regressions in which the dependent variable is the excess mortgage interest rate, which is the difference between the mortgage rate at origination and the average rate of all mortgages generated in the same quarter . The regression is run on a cross-sectional sample that comprises all mortgages at origination in the Freddie Mac database from January 2012 until December 2017. The explanatory variables include *Credit Score*, which is a borrower's credit score at origination. The *Debt-to-Income* ratio measures how much of a borrower's income goes towards paying off their debts every month. It is calculated by dividing the total monthly debt payments, including the mortgage and other loan repayments, by the total monthly income reported when underwriting the mortgage. *Loan-to-Value* is the ratio between the mortgage balance at origination and property price derived from the relevant state-level House Price Index. *Joint* is a dummy variable that captures loans with more than one borrower. ρ is the implied mortgage correlation derived from crisis period default rates and long run default rates with Equations 4.1 to 4.3 and with mortgages originated up to December 2011. Macroeconomic factors (yearly change in State-level Unemployment and House Price Index), used as a proxy of economic activity at the time of origination, are included in the regression and reported as Macro controls. *Region* FE are regional fixed effects in which regions are obtained from the US state groupings produced by the US Bureau of Economic Analysis (BEA); *Non-recourse* FE are fixed effects that identify non-recourse states. *Bank* FE are fixed effects that identify the largest mortgage lenders in the Freddie Mac sample. *Purpose/Occupancy* FE are fixed effects that identify the purpose for which the mortgage was taken out (i.e. cash-out refinance, no cash-out refinance or purchase, as well as the occupancy status (i.e. investment, primary home or second home); *First Time* FE identifies mortgages taken out by first time buyers; *Property* FE are fixed effects that identify the number of units in the property and the type of property (i.e., Condo, Co-op, manufactured housing, planned unit development or single-family). In parenthesis we show robust standard errors. Data frequency is quarterly. ***, **, * denote statistical significance at the 1%, 5% and 10% levels respectively.

Variables	Model 1	Model 2	Model 3
Credit Score	-0.0019***	-0.0019***	-0.0019***
	(0.000)	(0.000)	(0.000)
Loan-to-Value	0.0063***	0.0062***	0.0062***
	(0.000)	(0.000)	(0.000)
Debt-to-Income	0.0024***	0.0026***	0.0026***
	(0.000)	(0.000)	(0.000)
Joint	-0.0441***	-0.0439***	-0.0440***
	(0.000)	(0.000)	(0.000)
ρ	1.0183***	0.4699***	-0.9464***
		(0.021)	(0.076)
ρ*BB&T			1.9177***
			(0.108)
ρ*Chase			-2.9899***
			(0.093)
ρ*Citi			-0.6605***
			(0.140)
ρ*FifthThird			2.2298***
			(0.196)
ρ*Provident			1.4351***
			(0.160)
ρ*SunTrust			1.8623***
			(0.144)
ρ*UsBank			3.454***
			(0.092)
ρ*WellsFargo			0.4684***
			(0.083)
ρ*Other Sellers			2.2724***
			(0.077)
Constant	1.3625***	1.3211***	1.3499***
	(0.003)	(0.003)	(0.000)
Macro Controls	Yes	Yes	Yes
Bank FE	No	Yes	Yes
Region FE	Yes	Yes	Yes
Non-Recourse FE	Yes	Yes	Yes
Purpose/Occupancy FE	Yes	Yes	Yes
First Time FE	Yes	Yes	Yes
Property FE	Yes	Yes	Yes
Observations	7,680,619	7,680,619	7,680,619
Adjusted-R^2	22.54%	23.41%	23.53%

Table 3.11: Correlation and Excess Mortgage Interest Rates by Lender

This Table reports the regressions in Table 3.10 for each lender separately. The dependent variable is the excess mortgage interest rate, which is the difference between the mortgage rate at origination and the average rate of all mortgages generated in the same quarter. The regression is run on a cross-sectional sample that comprises all mortgages at origination in the Freddie Mac database from January 2012 until December 2017. ρ is the implied mortgage correlation derived from crisis period default rates and long run default rates with Equations 4.1 to 4.3 and with mortgages originated up to December 2011. Mortgage Controls include *Credit Score*, *Debt-to-Income* ratio, *Loan-to-Value* and *Joint*. The *Credit Score* is a borrower's credit score at origination. The *Debt-to-Income* ratio measures how much of a borrower's income goes towards paying off their debts every month. It is calculated by dividing the total monthly debt payments, including the mortgage and other loan repayments, by the total monthly income reported when underwriting the mortgage. *Loan-to-Value* is the ratio between the mortgage balance at origination and the current property price derived from the relevant state-level House Price Index. *Joint* is a dummy variable that captures loans with more than one borrower. Macroeconomic factors (yearly change in State-level Unemployment and House Price Index), used as a proxy of economic activity at the time of origination, are included in the regression and reported as Macro controls. *Region* FE are regional fixed effects in which regions are obtained from the US state groupings produced by the US Bureau of Economic Analysis (BEA); *Non-recourse* FE are fixed effects that identify non-recourse states. *Bank* FE are fixed effects that identify the largest mortgage lenders in the Freddie Mac sample. *Purpose/Occupancy* FE are fixed effects that identify the purpose for which the mortgage was taken out (i.e. cash-out refinance, no cash-out refinance or purchase, as well as the occupancy status (i.e. investment, primary home or second home); *First Time* FE identifies mortgages taken out by first time buyers; *Property* FE are fixed effects that identify the number of units in the property and the type of property (i.e., Condo, Co-op, manufactured housing, planned unit development or single-family). In parenthesis we show robust standard errors. Data frequency is quarterly. ***, **, * denote statistical significance at the 1%, 5% and 10% levels respectively.

Variables	BankofAmerica	BBAndT	JPMorganChase	Citi	FifthThird	Provident	SunTrust	USBank	WellsFargo	OtherSellers
ρ	-1.1381***	2.5277***	-6.0108***	-0.3661**	0.5623**	5.958***	1.1705***	3.8724***	-0.7462***	1.1007***
	(0.101)	(0.100)	(0.077)	(0.170)	(0.248)	(0.187)	(0.167)	(0.072)	(0.049)	(0.028)
Mortgage Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Macro Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Non-Recourse FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Purpose/Occupancy FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
First Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Property FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	348,815	352,683	509,201	71,736	77,628	117,602	96,859	560,804	1,178,851	4,366,440
Adjusted-R^2	15.27%	19.46%	21.25%	21.02%	22.47%	13.07%	20.83%	20.24%	25.54%	24.60%

Chapter 4

Loan Modifications and their Effectiveness: An Expanded View

4.1 Introduction

Mortgage modifications are a useful alternative to avoid foreclosure for distressed borrowers. They involve the renegotiation of contractual terms to facilitate obligors in managing the revised repayment schedule, thereby enabling them to fulfil their credit obligations. This process allows mortgagors to retain their properties, mitigating socio-economic repercussions such as the impact on local house prices (Campbell et al. (2011*a*), Towe and Lawley (2013) and Turnbull and van der Vlist (2023)) and default contagion (Goodstein et al. (2017) and Gupta and Hansman (2022)). It also reduces potential losses for lenders or investors arising from auction sales or missed payments.

Although mortgage renegotiation seems a quite common option nowadays, this practice was not widespread prior to the Global Financial Crisis (GFC). The low-default environment did not encourage lenders and servicers to renegotiate mortgage terms, as foreclosure was deemed less costly (Ambrose and Capone (1996), Adelino et al. (2013), Riddiough and Wyatt (1994) and Wang et al. (2002)). However, the surge in mortgage defaults during the GFC, coupled with the risk of millions of borrowers losing their homes, prompted a change in this approach. Policymakers and lending institutions were compelled to explore alternatives to foreclosure to stabilize the teetering financial system. Initially cautious, lenders and servicers gradually expanded their offerings to include changes to mortgage contractual terms (Cutts and Merrill (2008)). The introduction of government initiatives, such as the Home Affordable Modification Program

(HAMP) (U.S. Department of the Treasury (2023*a*)), further incentivised and standardized modification procedures.

However, what happens once modification is granted? Are borrowers effectively helped to keep up with payments, despite the already proven inability in doing so? How efficient have been the programs designed to support borrowers and lenders in providing payment relief? Academic research attempted to respond to these questions from different angles, particularly in the wake of the Global Financial Crisis.

A primary thread of literature has assessed the impact of different types of modifications on post-renegotiation outcomes. Alterations in contractual terms can be implemented in various ways, such as reducing the interest rate, lengthening the loan term, or decreasing the principal amount. Pioneering studies by Quercia and Ding (2009), Haughwout et al. (2009), and Goodman et al. (2011) examined the correlation between payment relief and re-default rates post-modification, establishing a positive relationship between decreased payment obligations and lower re-default rates. Further research expanded on this dynamic by incorporating socioeconomic and demographic factors (Boehm and Schlottmann (2020), Collins et al. (2015), and Voicu et al. (2012)). Lastly, government initiatives like Home Affordable Modification Program (HAMP) have significantly influenced the renegotiation landscape and post-modification resolutions. Schmeiser and Gross (2016), Voicu et al. (2011), and Scharlemann and Shore (2016) have contributed to this literature, demonstrating a positive correlation between these programs and successful borrower performance.

Despite the valuable contributions of prior research, certain limitations exist. A significant portion of the literature has focused on subprime borrowers from single lenders or privately securitised transactions (Quercia and Ding (2009), Schmeiser and Gross (2016), Chan et al. (2014) and Voicu et al. (2012)). This focus is not without consequences for representativeness[1] and the range of modification types considered. For

[1] The quarterly average of subprime mortgages originated from 2003 up to 2023 is 12%. If considering 2023 alone, this value drop to 8%. Please refer to Federal Reserve Bank of New York (2024).

instance, these studies underscore the effectiveness of principal reduction as a modification measure. Yet, this approach is not universally applicable; it is pertinent to portfolios or privately securitised loans but not to mortgages backed by Government Sponsored Enterprises (GSEs) that are ineligible for a balance decrease[2]. Conversely, research involving mixed portfolios, encompassing both privately securitised and government-sponsored loans, has been geographically specific (Haughwout et al. (2009) and Voicu et al. (2011)). This specificity may yield insights that are representative of a single jurisdiction, thereby neglecting state-level variations that could influence post-modification outcomes. In this paper, we examine post-modification outcomes for conventional loans securitised by Freddie Mac on a national scale, an area under-explored in the existing literature. This focus is significant given that GSE loans constitute a substantial segment of the mortgage market (66% of the total, according to Fuster et al. (2022) and Banking Strategist (2022)). Understanding their post-modification performance is crucial for lenders and investors as it provides insights into the "prime" segment of mortgage balance-sheets (Adelino et al. (2016)).

This chapter contributes to extant literature by highlighting the difference in borrowers, loans and modification type characteristics in influencing post-modification resolutions for GSE mortgages. Our findings corroborate that post-modification outcomes are enhanced by payment decreases, even in the absence of principal reduction, and when changes are limited to interest rate and term extension as in the case of GSE loans. Moreover, we demonstrate that some borrowers and loan features carry a different impact, compared with exiting papers.

Secondly, most studies have examined the role of mortgage renegotiations in the aftermath of the Global Financial Crisis (GFC). When more recent data is employed, the primary focus is to comprehend the impact of the Home Affordable Modification Program (HAMP) on post-modification outcomes (Agarwal et al. (2017), Goodman et al. (2013), Schmeiser and Gross (2016) and Voicu et al. (2012)). However, HAMP

[2] Principal reduction was granted to underwater GSE borrowers under the Home Affordable Repurchase Program (HARP). However, HARP determined the loan being refinanced and not simply modified, which instead is our area of interest.

was discontinued in 2016, yet mortgage modifications continued to be offered to distressed borrowers, even in periods of financial stability (2016-2020) and during the COVID-19 pandemic. It is therefore of significant importance to comprehend how mortgage renegotiations have been incorporated into the market over the long term, and whether they remain an effective measure during stressful periods not necessarily characterized by a default surge. For instance, in an improved economic environment, were less generous modifications still beneficial? Answering this question is vital as it enhances our understanding of effective renegotiations in risk management, whether in a ”tranquil” period or during a different economic shock. Indeed, the HAMP era may have been marked by unique borrowers behaviour and policy overreaction, which may not be indicative of a long-term scenario. We contribute by showing several implications of HAMP cessation on post-modification outcomes, and how the cease of the program determines a behavioural change in borrowers in post-modification resolutions. We show that post-HAMP modifications exhibit mixed behaviour. Specifically, we discover that interest rate reductions have become more effective and better targeted than term extensions. We also show that HAMP-eligible modifications exhibit a poorer performance over a long-term period.

As a corollary, we further investigate post-renegotiation outcomes of loans modified during Coronavirus Aid, Relief, and Economic Security Act (CARES Act). Despite the program only offering payment moratorium to distressed mortgagors, rather than permanent modifications as in HAMP, it is relevant to examine this period due to its temporary impact and behavioural discontinuity of borrowers and lenders. This investigation aids in unveiling the dynamics of mortgagors genuinely requiring renegotiation. We contribute to academic research by demonstrating that lenders, servicers, and agencies have effectively mastered strategies to assist borrowers facing financial hardship. They have aptly targeted mortgagors necessitating long-term modifications, without including those that merely seek strategic payment relief.

Furthermore, we offer a long-term perspective on post-modification outcomes. While much of the existing literature is confined to a 12-month horizon (Quercia and Ding

(2009)) or, due to the sample used, extends to a maximum of 2 years (Voicu et al. (2011)), the prolonged nature of mortgage agreements necessitates a more extensive observation period to accurately discern the ultimate post-modification outcome, particularly in relation to foreclosures or prepayments. The data used in our analysis enables us to bridge this gap and provide a more comprehensive view of post-modification outcomes, thereby facilitating a more thorough examination of foreclosures and prepayments, which typically necessitate a longer observation window to fully materialise.

4.2 Data

This study employs loan-level and borrower-level data on nearly 500k modified mortgages. The dataset includes fully amortizing fixed-rate, single-family mortgages originating from the first quarter of 1999 through the third quarter of 2022. These mortgages were issued by over 100 lenders and subsequently acquired by Freddie Mac for securitization purposes. The loan status is tracked until the second quarter of 2023. Consistent with the demographic distribution in the United States, states such as California, Florida, Texas, Illinois and New York have a larger representation within the sample (Figure 4.1).

Loans performance is monitored with monthly frequency since the date of origination. *Delinquency Status*, *Interest Rate* and *Unpaid Balance* are regularly updated throughout the entire lifetime of the loan. The availability of performance variables helps us to determine the evolution of each mortgage's credit performance and collateral information.

Among the key performance variables, the *Modification Flag* is instrumental in identifying loans that have undergone renegotiation. This flag is updated whenever there are changes to the mortgage contractual terms, thereby facilitating the tracking of multiple modifications for a single loan. Once a mortgage is modified, it can be ascertained whether the modification influenced the interest rate, loan term, or outstanding balance. This is achieved by comparing the value at time of modification with the preceding month's value[3]. The volume of mortgage modifications remained relatively low prior to 2009, but saw a substantial surge from 2010 onwards, as depicted in Figure 4.2a. After peaking in 2010, the number of renegotiations began to steadily decline, yet the volume remained significant and never reverted to pre-HAMP levels. The COVID-19 pandemic years (2020 and 2021) witnessed the fewest number of modifications post-GFC, likely due to the enactment of payment moratorium under CARES Act. The majority of modified mortgages were originated prior to 2009 (see Figure 4.2b), consistent with HAMP eligibility criteria (U.S. Department of the Treasury (2023*a*)). Nevertheless, given that renegotiations were also extended to other mortgagors regardless of HAMP eligibility and after the program discontinuation, more recent vintages are also represented in the sample.

In a significant number of instances (14% of all renegotiations), the initial modification proves insufficient, necessitating additional allowances for the borrower to maintain repayments. Table 4.5 indicates that loans modified on a single occasion constitute 85.68% of the population. In contrast, mortgages modified two, three, and four times account for 12.03%, 2.10%, and 0.18% of the sample, respectively. Figure 4.3 distinctly indicates that older vintages are more likely to receive extra modifications, partially attributable to the extended observation window. This study limits our sample to a maximum of four modifications. Various reasons could account for subsequent renegotiations; for instance, loans altered in the pre-HAMP era might have enhanced their contractual terms following the amendments introduced by government policy. Interest rate resets (Scharlemann and Shore (2022)) of HAMP loans also partially cause subsequent modifications. Table 4.5 also reveals that the proportion of modifications involving interest rate increase escalates with the number of renegotiations, in contrast to all other types of renegotiations.

Table 4.4 delineates the evolution of modification types. Predominantly, the years preceding HAMP saw a surge in balance increases, primarily due to arrears being added to the outstanding balance, often coupled with term extensions. From a re-

[3] Or preceding months, as the updated value may be lagged in some instances.

payment perspective, an increase in the balance cannot be regarded as a mortgage modification that benefits the borrower, as it does not lead to a reduction in monthly instalments. However, this type of modification prevents the accumulation of arrears, which precludes the initiation of foreclosure and repossession procedures. Under this angle, balance increase is a supportive measure for mortgagors in financial trouble that wish not be foreclosed. Between 2009 and 2014, the focus shifted towards interest rate reductions, albeit rarely in isolation, and commonly in conjunction with term extensions and balance increases. Post-HAMP, i.e., in the years succeeding 2016, the trend reverted, with term extensions and balance increases becoming prevalent. However, interest rate reductions persisted, reflecting HAMP's enduring influence. Notably, our sample did not include any loans that underwent balance reductions, consistent with GSEs' policies.

Over the years, modifications in interest rates and term extensions have varied. During the initial period of the program, substantial interest rate reductions were granted, averaging a decrease of 2.5%. However, in the following years, these reductions became progressively less substantial, stabilising at an average level shortly after 2015 (Figure 4.4a). Conversely, term extensions displayed a distinct trend, consistently increasing over time until reaching a point of equilibrium at the conclusion of the HAMP period (Figure 4.4b), consistent with the beginning of GSE Flex Program.

The distribution of loan termination by year of modification is illustrated in Figure 4.5. Although some loans in the sample remain active at the end of the observation period, and are consequently unrepresented in the graph, termination events can be identified for 78% of the loans in our sample and for 90% of the loans modified prior to 2017. Six primary categories classify these termination events: *Liquidation*, *Prepaid/Matured*, $Modification$, $Reperforming$, *60+Delinquent*, and *Current*.

The *Liquidation* category denotes the sale of the property, either by the lender or a third party, representing the most severe potential outcome[4]. *Zero Balance Code*

[4] *Liquidation* is triggered once one of the following values is assigned: REO (Real Estate Owned) Disposition, Short Sale or Charge Off.

helps to identify *Liquidation* post-modification outcome, and it is triggered once one of the following values is assigned: REO (Real Estate Owned) Disposition[5], Short Sale[6] or Charge Off[7] or Third Party Sale[8], which all identify property liquidation. *Liquidation* is the most severe final status both for borrower and lender, as it entails the borrower's property seizure and a resulting potential loss for the credit institution. *Prepaid/Matured* indicates a voluntary pay-off, either due to the borrower refinancing elsewhere or completion of all payments. *Reperforming* refers to the sale of a reperforming loan conducted by Freddie Mac. *60+Delinquent* signifies the loan's delinquency status. Loans modified in the immediate aftermath of the GFC exhibit a higher likelihood of foreclosure, a trend possibly linked to the extended observation horizon. However, our primary focus is to understand the factors that influence the potential post-modification outcomes, with particular emphasis on the type of modification received by the borrower.

In addition to modification information, additional data on both origination and performance can help profiling each mortgage in the sample. Origination data includes borrower-, property- and mortgage-related characteristic measured at the time of issuance. Characteristics of modified mortgages are shown by year of modification in Table 4.2 and Table 4.3.

Table 4.2 indicates that the majority of borrowers who receive a modification are purchasing primary residences, while a significantly smaller part buys investment or second homes. This aligns with the initial eligibility criteria of HAMP (U.S. Depart-

[5] Real Estate Owned (REO) acquisition refers to foreclosed properties that are owned by the lender and were not sold at an auction.

[6] A short sale in real estate is an offer of a property at an asking price that is less than the amount due on the current owner's mortgage. A short sale is usually a sign of a financially distressed homeowner who needs to sell the property before the lender seizes it in foreclosure.

[7] A charge-off refers to an accounting action taken by a lender when they determine that a borrower's home loan is unlikely to be collected. This usually occurs after the borrower has been significantly delinquent on payments. It often precedes foreclosure.

[8] A third party sale refers to a transaction where a property is sold to a third party, which is typically not the original lender or the homeowner. This generally happens when the borrower cannot keep-up with repayments and the mortgage is hence foreclosed.

ment of the Treasury (2023*a*)), which limited modifications to borrowers who intended to use the house as their main dwelling. The conclusion of HAMP at the end of 2016 resulted in a rise in the proportion of other occupancies. The *Loan Purpose* exhibits an interesting increase in refinance mortgages during modifications immediately following the GFC, likely due to the falling interest rate environment. Conversely, the share of purchase mortgages has seen an increase in recent years. The *Channel* variable has seen a reduction in *Third-Party-Originations* (TPOs). This category is solely applicable to mortgages originated prior to 2008, as Freddie Mac began gathering detailed information required to disclose whether a Broker or Correspondent was involved in the origination of each loan from that year onwards. Another noteworthy trend is the significant increase in the proportion of First-Time-Homebuyers in modified mortgages post-2017, mirrored by an increase in the share of Single borrowers during the same period.

Table 4.3 displays the distribution of *Credit Score*, *Loan-to-Value (LTV)*, *Debt-to-Income* and *Interest Rate* by year of modification. The *Credit Score* refers to the FICO score, indicating that recipients of modifications comprise a blend of prime and subprime borrowers. The *Debt-to-Income* ratio represents the sum of borrower's monthly debt payments, including housing expenses related to the underwritten mortgage, divided by the total monthly income used to underwrite the loan. The average *Debt-to-Income* of borrowers receiving a modification is higher than the average of the entire population. *Original Loan-to-Value* is calculated as the ratio of the mortgage loan amount to the appraised value of the property at origination and is reported by year of modification. The average seems quite stable over time, with borrowers seeking a modification being on an average of 80% LTV at origination. Conversely, the *Updated Loan-to-Value* ratio is calculated by dividing the current mortgage loan amount by the appraised value of the property at the time of modification. This ratio provides a more accurate reflection of the borrower's remaining repayment commitment relative to the equity held in the property at the time of observation. Consequently, the *Updated Loan-to-Value* ratio is a preferable metric to the *Original Loan-to-Value* ratio, as it more effectively identifies instances where the borrower owes more than the property's value, which can subsequently influence post-modification behaviour. Notably, loans modified immediately following the Global Financial Crisis (GFC) exhibit higher *Updated Loan-to-Value* ratios compared to those modified in later periods. However, it is crucial to recognise that the appraised property value (i.e., the denominator of the *Updated Loan-to-Value* ratio) at the time of modification or any subsequent period is derived from changes in the House Price Index (HPI) at the state level from the origination to the point of observation. The reliance on state-level HPI introduces limitations, as it lacks the granularity to accurately reflect the variability in house prices that would be captured by employing Metropolitan Statistical Area (MSA) or ZIP code level data. This approximation leads to outliers that disproportionately influence the limited post-modification population analysed here, compared to the dataset utilised in Chapter 3. Therefore, to avoid instability in the final estimations due to the small sample size and the approximation of the *Updated Loan-to-Value* ratio, the *Original Loan-to-Value* ratio is ultimately used. Employing the latter metric does not provide the benefits of using more recent information; however, it offers greater stability and accuracy, ensures error-free calculations, and remains a sufficiently accurate measure of the borrower's debt burden relative to the property's appraised value.

It clearly stands out that there is a shift in population characteristics when considering renegotiations granted well after the GFC, compared with those received in the peak of HAMP. Further scrutiny of these unique temporal intervals affords supplementary insight into post-modification outcomes during periods of relative financial stability.

4.3 Empirical Methodology

Our objective is to comprehend the factors influencing post-modification outcomes, necessitating a modelling approach that accommodates the multinomial nature of the target variable. Consequently, we utilise a discrete-time proportional hazard model with competing risks to scrutinise the impact of loan-level variables and modification measures on the different possible resolutions. The proportional hazard model with competing risks is estimated via a multinomial logistic regression, enabling the isolation of each covariate's effect on distinct targets. This methodology is frequently employed in this context (Voicu et al. (2012), Kelly and McCann (2016), Been et al. (2013) and Schmeiser and Gross (2016)).

Alternative methodologies were evaluated, including ordered logit models and distinct logistic regressions for each pair of outcomes. The ordered logit model necessitates an 'ordered' nature of the dependent variable, signifying an explicit ranking from lowest to highest risk. Despite its potential effectiveness, the risk ranking may not be uniquely identifiable. For instance, from the borrower's perspective, modification might be more advantageous than foreclosure, a principle that may not necessarily apply to a lender. As our analysis is intended to be impartial, representing consumer behaviour from a neutral standpoint, we reject this method since the chosen order might only mirror one of the multiple stakeholders involved (e.g., lender, borrower, policymakers). Moreover, the ordered logit model is valid only if the data fulfils the 'proportional odds assumption', a condition that is generally challenging to meet and might necessitate a significantly large sample size, which we cannot fully supply.

Another feasible approach is conducting separate logistic regressions for each pair of outcomes. However, this method may lead to running the analysis on varying samples (based on the pair under consideration). If we instead consider each target individually, the reference category could encompass a bundle of vastly different outcomes. Consequently, neither of these methodologies is deemed entirely appropriate for our analysis, and we prefer to rely on prevailing methodology observed in previous research.

On this scope, the data is first structured in a panel unbalanced form, where each loan's performance is monthly tracked from point of modification onwards. For this reason, each loan's observations are dropped before the point of modification, and all the information at origination is retained. Then, for each of the K possible outcomes, multinomial logistic regression is fitted as per Equation 4.1:

$$ln(\frac{Pr(Y_{it} = k)}{Pr(Y_{it} = K)}) = W_{it,k} \forall k < K \tag{4.1}$$

where:

$$Pr(Y_{it} = k) = \frac{e^{W_{it,k}}}{1 + \sum_{k=1}^{K} e^{W_{it,k}}} \forall k < K \tag{4.2}$$

$$Pr(Y_{it} = k) = \frac{1}{1 + \sum_{k=1}^{K} e^{W_{it,k}}} \forall k = K \tag{4.3}$$

with:

$$\begin{aligned} W_{it,k} = \alpha_k + \sum_{b=1}^{N_b} \beta_{b,k} LoanCharacteristics_{b,i(t)} + \sum_{c=1}^{N_c} \gamma_{c,k} Modification_{c,i(t)} + \\ \sum_{d=1}^{N_d} \delta_{d,k} State_{d,i} + \lambda_{l,k} Controls_{l,t} \end{aligned} \tag{4.4}$$

or:

$$\begin{aligned} W_{it,k} = \alpha_k + \sum_{b=1}^{N} \beta_{b,k} LoanCharacteristics_{b,i(t)} + \sum_{c=1}^{N} \gamma_{c,k} Modification_{c,i(t)} + \\ \sum_{d=1}^{N} \delta_{d,k} State_{b,i} + \zeta PostHAMP_t + \sum_{b=1}^{N} \eta_{b,k} PostHAMP_t \times LoanCharacteristics_{b,i(t)} + \\ \sum_{c=1}^{N} \theta_{c,k} PostHAMP_t \times Modification_{c,i(t)} + \sum_{d=1}^{N} \iota_{d,k} PostHAMP_t \times State_{d,i} + \\ \lambda_{l,k} Controls_{l,t} \end{aligned} \tag{4.5}$$

or:

$$\begin{aligned} W_{it,k} = \alpha_k + \sum_{b}^{N_b} \beta_{b,k} LoanCharacteristics_{b,i(t)} + \sum_{c}^{N_c} \gamma_{c,k} Modification_{c,i(t)} + \\ \sum_{d}^{N_d} \delta_{b,k} State_{b,i} + \zeta PolicyPeriod_t + \sum_{b}^{N_b} \eta_{b,k} PolicyPeriod_t \times LoanCharacteristics_{b,i(t)} + \\ \sum_{c}^{N_c} \theta_{c,k} PolicyPeriod_t \times Modification_{c,i(t)} + \sum_{d}^{N_d} \iota_{b,k} PolicyPeriod_t \times State_{b,i} + \\ \lambda_{l,k} Controls_{l,t} \end{aligned} \tag{4.6}$$

k signifies one of the established K outcomes. As outlined in Section 4.2, the mortgages in our sample can transition into any of the following states: $Current$, $Reperforming$, *Prepaid/Matured*, $Modification$, *60+Delinquent*, and *Liquidation*. Owing to the scarcity of observations or similarity of the outcomes, we merge certain categories to mitigate estimates volatility. The $Current$ and $Reperforming$ statuses are consolidated due to their similar performance characteristics. Moreover, given the infrequent re-modifications post-HAMP cessation (i.e., post-2016), *60+Delinquent* and $Modification$ are combined into a single category. These events denote a borrower's adverse behaviour, distinctly separate from $Current$, *Prepaid/Matured*, or $Liquidation$. Consistent with prior literature (Schmeiser and Gross (2016)), we designate $Current$ status as the reference category, as modified loans have their status set to $Current$ following modification.

The subscript t in loan characteristics is enclosed in brackets, signifying that only a subset of these characteristics are time-dependent. Amongst the explanatory drivers[9], *LoanCharacteristics* indexed with b include features related either to the borrower, such as credit score, debt-to-income, first-time homebuyer, or related to the mortgage, such as original loan-to-value and purpose. $Controls$ includes macro-sensitive factors, such as 12 month unemployment rate (lagged by 2 years) and interest rate spread, which is the difference between interest rate at origination and Freddie Mac 30Yr mortgage rate. $Modification$ denotes the key characteristics indexed with c of the mortgage modification that are relevant for our analysis: (a) interest rate reduction, (b) term extension and (c) maximum delinquency prior to modification, which represents the maximum number of months in arrears prior to modification. Finally, we consider *State* variability indexed with d by including relevant information related to (a) geographical location, (b) recourse versus non-recourse legislation [10] and (c) judicial versus non-judicial legislation[11]. If a loan undergoes re-modification, we designate modification as a terminal status and commence tracking the new performance from the new point of modification onwards.

[9] For a full list of the model variables and their explanation, please refer to Table 4.1.

[10] In recourse jurisdictions the lender, in the event of a foreclosure, can go after the borrower for any remaining balance left after the property is sold. To identify states with non-recourse legislation, we referenced the definition in Nam and Oh (2021).

[11] Judicial states are those U.S. states where a lender is obliged to go through the court system to initiate the foreclosure process of a home. To identify states with judicial/non-judicial law, we referenced the definition in Ding et al. (2022), who use the classification provided by the National Consumer Law Center (NCLC) (National Consumer Law Center (NCLC) (2022)).

The multinomial logistic regression has been executed under three distinct configurations, as indicated by Equation 4.4, Equation 4.5, and Equation 4.6. Equation 4.4 applies to the complete sample, without any differentiation concerning policy periods. Conversely, as per Equation 4.5, the dummy $PostHAMP_t$ activates for modifications granted from 2017 through 2023, inclusive. This is designed to measure the influence of the HAMP lift on post-renegotiation outcomes and its effect on each explanatory factor. A final estimation follows Equation 4.6, utilising the same framework but further distinguishing mortgages modified during the post-HAMP period from those renegotiated during the CARES Act, from March 2020 to September 2021. The $PolicyPeriod_t$ dummy variable thus assumes three unique values, each representing a specific period under investigation. The objective is to differentiate those mortgages that sought a modification in spite of the opportunity to request a forbearance period granted by the CARES Act in response to the pandemic.

Predominantly, literature employing multinomial logistic models (Schmeiser and Gross (2016), Voicu et al. (2012) and Kelly and McCann (2016)) presents findings in terms of *Relative Risk Ratios* (*RRR* or *Odds*), calculated via exponentiating the log-odds estimated by Equation 4.1. The *Relative Risk Ratio* quantifies the ratio of the likelihood of selecting outcome k to that of opting for the baseline category (here, *Current*). *Relative Risk Ratios* offer straightforward interpretation, as they directly contrast the impact of a one-unit augmentation on probability ratios. We report results in this format, to allow a direct comparison of the non-interacted terms with results reported in Schmeiser and Gross (2016) as *Relative Risk Ratios.* On the other hand, when an interaction term is introduced between all characteristics and the dummy $PostHAMP$ (or $PolicyPeriod$), interpreting results in odds can become challenging (Ai and Norton (2003)) due to non-linearities. As a result, we prefer employing average marginal effects for commenting model estimations, in particular for the interacted terms. Lastly, we employ robust standard errors, clustered by loan identifier, to effectively control for unobserved heterogeneity and its dependence from repeated observations for the same mortgage.

4.4 Results

Table 4.8 to Table 4.11 display the outcomes of the multinomial logistic regressions. As previously outlined in Section 4.3, we mainly discuss average marginal effects rather than *Relative Risk Ratios* to account for the non-linearities introduced by the interaction term. Nonetheless, *Relative Risk Ratios* are provided for a more direct comparison of the non-interacted terms with extant literature. The first column reports the estimates of the post-modification outcome labelled as *Prepaid/Matured*, followed by the average marginal effects of *60+Delinquent* and finally, *Liquidation*. The *Current* category is excluded, serving as the reference status.

Generally, distinguishing between continuous and categorical variables is crucial when interpreting model outcomes. The marginal effects of categorical variables, constructed as dummy variables in our sample, are relatively straightforward to comprehend in terms of their economic significance. Indeed, the reported results depict the impact of an activated dummy variable (i.e., a one-unit increase from 0 to 1) on the probability of the outcome considered. On the other hand, for continuous variables, the economic significance of a one-unit increment is less straightforward as it depends on the range of values assumed by the variable of interest. Consequently, results provided in this section will consider a specific, meaningful change for the variable in question. Finally, it is also noteworthy that the sample is constructed as a panel with multiple observations for the same account. While *Current* and *60+Delinquent* are repeated statuses throughout the observation window, *Prepaid/Matured* and *Liquidation* represent terminal events. Hence, their marginal effects will be comparatively lower than the other two.

Our first focus lies on the first model that clearly distinguishes the HAMP from post-HAMP period. We first deep dive into the non-interacted coefficients in Table 4.8 (Table 4.9), representing the marginal effects (*Relative Risk Ratios*) of modifications implemented during the active phase of the HAMP program (or just prior to it) on post-modification outcomes. We have not separately modelled the pre-HAMP period due to a scarcity of modifications. As shown in Table 4.8 (Table 4.9), the marginal effects (odd ratios) of non-interacted terms closely resemble those in Table 4.6 (Table 4.7) and Table 4.10 (Table 4.11), since the HAMP period accounts for the majority of modifications in the sample. Comparing the non-interacted terms is critical at this stage and serves a dual purpose. Firstly, it offers the most direct comparison with reference papers, such as Schmeiser and Gross (2016), which provide the closest possible analysis. We aim to determine if there are significant differences between the two studies on the overlapping period, or if similar trends can be observed, to ensure that either the findings from both can be generalised or should be differentiated in terms of the mortgage market's representativeness over time instead. Given the differences in data and model framework, the comparison is only made for those common variables and outcomes. Secondly, the analysis assists in identifying the overall robustness of the explanatory characteristics used, which may be slightly weakened by policy breaks due to fewer observations.

Among loan characteristics, variables such as *Credit Score*, *Loan-to-Value*, *Joint*, and *Third Party Origination* are important for their statistical and economic significance. A 50-point increase in *Credit Score* elevates the probability of prepayment by 6.9 bps, while simultaneously decreasing the likelihood of default and repossession by 2.57% and 1.6 bps respectively. *Loan-to-Value* is more influential than the score in determining repossession status. A 20-point increment in *Loan-to-Value* (i.e., from 60% to 80%) raises the likelihood of repossession by 9.1 bps, and the probability of delinquency post-modification by 1.09%. A higher *Loan-to-Value* also inversely affects the ability to prepay, as the same increase results in a 9.1 bps reduction in prepayment probability. The observed trends are in accordance with the findings of Schmeiser and Gross (2016) and Voicu et al. (2011)[12], despite the authors' preference for a distinct methodology, which involves segmenting the variables into categorical ranges. The impact of *Debt-to-Income* is less pronounced, with a 10-point increase (i.e., from 25% to 35%) elevating the likelihood of delinquency by 16 bps and repossession by 1.1 bps. This aligns with findings from Foote et al. (2010), who found that borrowers' default

[12] It should be noted that Voicu et al. (2011) solely considers re-default rates, whereas Schmeiser and Gross (2016)'s analysis is more comprehensive, encompassing foreclosure filing, modification, REO/foreclosure sales, and short pay-off as potential post-modification outcomes.

choices are influenced more by current/future income than by debt-to-income at origination. Despite we are examining post-modification scenarios, this finding from Foote et al. (2010) remains relevant within our context.

The categorical variables *Joint*, *Third Party Origination*, and *Refinance*, likewise influence post-modification outcomes during HAMP. When a mortgage modification involves multiple borrowers, the probabilities of post-modification outcomes shift notably. The likelihood of prepayment escalates by 8.9 basis points, while the probabilities of delinquency and foreclosure decrease by 1.97% and 5.5 basis points, respectively. Conversely, loans categorised as *Third Party Origination* exhibit a significant rise in foreclosure likelihood by 5.2 basis points. It's crucial to acknowledge the correlation between third-party origination loans and their issuance date, as discussed in Section 4.2. These loans often lack comprehensive documentation and full transparency, which aligns with their enduring risky profile, even after a modification intended to assist in repayment. Lastly, *Purchase* loans demonstrate an increased propensity towards delinquency and foreclosure (1.75% and 3.6 basis points respectively), consistent with Schmeiser and Gross (2016). Upon examining the odds (Table 4.9), the impact's magnitude is greater in Schmeiser and Gross (2016), where the likelihood of transitioning into delinquency is elevated by 21% compared to maintaining a current status, as opposed to the 14% increase noted in the Freddie Mac Data. At the same time, the probability of foreclosure is amplified by 46% in comparison to maintaining a current status, as opposed to our 13%. This discrepancy may be attributed to the distinct nature of the samples, as subprime mortgages are less likely to remain current post-modification, thereby escalating the probability of alternative outcomes.

The post-modification outcomes are also significantly influenced by state-level laws. Mortgages from *Judicial* states are 2.36% more likely to revert to default status post-modification, and they are 9.1 bps less inclined to prepay. This observation directionally aligns with Schmeiser and Gross (2016), although the odds of delinquency are much higher in our sample (1.18 versus 1.04). In contrast, the escalation in foreclosure probability is virtually insignificant (0.19 bps). Although this contrasts with Schmeiser and Gross (2016), whose odds of foreclosure in *Judicial* states are significantly high, it corresponds with Ding et al. (2022), who argue that judicial procedure typically offers borrowers additional opportunities to reinstate their mortgage outside of foreclosure or liquidation, thereby diminishing the effect of these drivers on foreclosure probabilities. Conversely, mortgages in *Non Recourse* states display an opposite pattern. The probability of post-modification delinquency decreases by 1.87%, while the likelihood of prepaying increases by 6.6 bps. This concurs with Schmeiser and Gross (2016), who does not elaborate on this finding, but it contradicts a broader literature that identifies mortgages in non-recourse states as riskier (Nam and Oh (2021)). However, although higher likelihood in defaulting across non-recourse states is sound, we must bear in mind that we are examining a slightly different behavioural phenomenon. The borrowers in our sample are already in a vulnerable position, and the sensitivity to *Non Recourse* or *Recourse* laws might actually invert since we are not dealing with strategic defaulters any longer, but with homeowners striving to maintain their mortgage payments and retain their homes. A parallel may be drawn with the research conducted by Ghent and Kudlyak (2011), who demonstrates that the sensitivity to recourse laws in default behaviour changes based on the loan appraisal value. Analogously, in our context, modified mortgages could potentially display a differing sensitivity to recourse laws to more standard patterns, particularly when reverting to delinquency.

As anticipated, renegotiation terms also positively impact post-modification outcomes. Notably, HAMP-eligible mortgages demonstrate a beneficial effect by decreasing the likelihood of *Liquidation* by 15 bps during the policy's active period. These HAMP-eligible loans also display improved performance, being 1.6% less prone to enter *60+ Delinquent* status post-modification (Voicu et al. (2011) and Schmeiser and Gross (2016)). Moreover, a reduction in monthly payments also positively affects post-modification resolutions. This decrease in monthly instalments can be achieved either through interest rate reduction or an extension in the mortgage term, with each approach having a distinct impact. An average interest rate reduction of 25% (i.e., from 4% to 3%) results in a 5.64% decrease in the probability of entering a delinquency status post-modification, and a 5.5 bps decline in foreclosure likelihood. Conversely, a term extension, considering an average increase of 10 years, reduces the probability of delinquency by 3.2%, and foreclosure by 8.6 bps. Thus, term extension offers greater relief in preventing final mortgage repossession post-renegotiation, but less relief in avoiding delinquency. The probability of prepayment is diminished by these measures, aligning with the intuition that modifications in contractual terms encourage (or bind) borrowers to adhere to the existing repayment plan, thereby lessening the likelihood of voluntary mortgage termination ahead of schedule.

Lastly, we examine the *Maximum Delinquency* prior to modification and its correlation with post-modification outcomes. As *Maximum Delinquency* indicates the number of months in arrears, it is evident that each additional month spent in delinquency before the mortgage was modified escalates the probability of *60+ Delinquent* and *Liquidation* by 26 and 0.4 bps respectively, whilst decreasing the probability of prepayment by 1 bps. This observation suggests that timely modifications are more effective in mitigating severe post-modification outcomes, compared to late interventions, in line with Calem and Sarama (2017).

We now analyse the influence of the same mortgage and modification characteristics following the cessation of HAMP program. This involves the interaction of the variable $PostHAMP_t$, activated for all mortgages modified post-2016, after the government's modification program concluded and alternative renegotiation schemes were incorporated into the mortgage system (Federal Home Loan Mortgage Corporation (FHLMC) (2024) and Federal National Mortgage Association (FNMA) (2024)). As detailed in Section 4.3, to comprehend the cumulative effect of a single-unit alteration of the predictors on post-modification outcomes, we examine marginal effects and, for coherence, we replicate the same unit(s)-increase applied previously for continuous variables.

Firstly, we confirm that key variables, such as *Credit Score* and *Loan-to-Value*, maintain a logical trend. This holds true for both variables, despite a decrease in the overall impact in absolute terms. A positive shift of 50 units in the *Credit Score* decreases the likelihood of delinquency by 1.89%, while it reduces the foreclosure rate by 3 bps.

Similarly, the influence of *Loan-to-Value* remains directionally consistent after the program cessation, exhibiting a positive correlation, albeit less significant than during the HAMP period. A 20-unit increase in *Loan-to-Value* escalates the probability of *60+ Delinquency* by 92 bps and of *Liquidation* by 2.4 bps. A consistent behaviour is observed in prepayment, where both variables preserve the direction but have a slightly diminished impact.

With regard to categorical mortgage characteristics, there have been pertinent shifts following the post-2016 amendments. *Joint* borrowers retain the trajectory of change, but exhibit a marked improvement in influencing delinquency performance. Indeed, the probability of transitioning into a *60+ Delinquent* status post-modification diminishes further by 3.34% (in contrast to a 1.97% reduction during HAMP). Conversely, the chances of prepayment and liquidation marginally increase, albeit maintaining a consistent directional trend. We also note an amplified influence of *Purchase* on delinquency behaviour, with the likelihood increasing by 2.43% (as opposed to 1.75%). On the other hand, *Purchase* loans display a marginal decrease in the likelihood of liquidation or prepayment when compared to the HAMP period (1.7 bps versus 3.6 for liquidation, 4.2 bps versus 5.1 for prepayment). On the other hand, *Third Party Origination* loans are 96 basis points more prone to become delinquent after a post-HAMP modification, compared to 1.4%, hence marginally improving. The impact of the same variable on *Liquidation* is disregarded, due to the likely bias from a scarcity of observations, thus diminishing its significance. We however observe that policy breaks, although not disrupting the impact of reduced payments, can affect their effectiveness quite substantially.

When it comes to state-laws, the influence of *Judicial* states on prepayment and liquidation behaviour is unchanged, whereas a contrary trend is observed for its impact on *60+ Delinquent* status. This shift in behaviour may underscore alterations to state-level policies that we cannot fully comprehend. Conversely, mortgages issued in *Non Recourse* states demonstrate a uniform behaviour in post-modification delinquency and prepayment, even when renegotiated after the cessation of HAMP. The probability of prepayment further increases by 7.4 bps, whilst it reduces to 74 bps and to 0.6 bps in relation to delinquency and liquidation respectively. Analogous to *Judicial*, the significance of foreclosure by *Non Recourse* is diminished. The coherence in post-modification behaviour of *Non Recourse* corroborates our prior consideration regarding a shift in sensitivity to recourse laws, attributable to the characteristics of the observed borrowers.

Finally, we discuss the influence of renegotiation practices on post-HAMP modified mortgages. Beginning with interest rate reduction and term extension, we find that the effects remain intuitively consistent with the HAMP period, although varying in magnitude depending on the variable under consideration. The impact of interest rate reduction on delinquency appears to be more pronounced, with a 25% reduction resulting in a 6.23% decrease in the likelihood of default following modification (compared to a 5.64% reduction during HAMP). This may highlight an enhancement in renegotiation offerings over time, by refining the targeting of borrowers and better tailoring the type of modification over a short-term. On the contrary, term extension plays a lesser role in preventing post-default delinquency, yet it continues to indicate that lowered monthly payments can help prevent post-modification delinquency. The impact of these two variables on foreclosure remains directionally consistent for term extension, but reverses for interest rate changes. This implies that, over extended periods, payment reductions via interest rate changes may be less effective than term extensions. Alternatively, this type of modification may be granted to particularly distressed borrowers who eventually surrender home ownership, thereby revealing a potential area for improvement in the allocation of mortgage modifications. In any case, we observe a non-constant behaviour in mortgagors, indicating a change in sensitivity due to the time period under examination.

Very importantly, the relevance of timely behaviour in granting modification is reaffirmed by the consistent significance of *Maximum Delinquency*, mirroring the pre-HAMP period. This suggests that timely modifications remain beneficial irrespective of policy alterations. Overall, it is evident that providing payment relief to borrowers continues to be an effective strategy to prevent further delinquencies, even after large government programmes have ended and lenders/GSEs have incorporated modifications into their systems, although we observe some changes that risk managers should attentively monitor over time.

A final consideration must be made on the reversed side of HAMP coin, specifically when examining loans eligible under HAMP that were re-modified following the program's termination. The probability of delinquency now alters, increasing by 4.23%. This is entirely reverse to the trend observed whilst the policy was operational, though statistically significant. Likely, such behaviour captures those mortgages that, despite renegotiations under HAMP, remained too precarious to maintain payments and necessitated further modification post-program, although too late to make it effectively affordable.

The results section is concluded by examining mortgages modified during CARES Act period, along with their subsequent post-renegotiation outcomes. Table 4.10 presents the final estimates of the multinomial logistic regression divided by the three different periods (HAMP, post-HAMP and CARES). Regarding the non-interacted part of the model, the findings are largely analogous to those in Table 4.8, reinforcing our confidence in the conclusions drawn so far. The same applies to the post-HAMP marginal effects. The interaction term pertaining to CARES, nevertheless, reveals interesting shifts in the determinants of post-modification resolutions. Given the shorter time frame under consideration, which precludes a comprehensive observation of foreclosures and prepayments, we restrict our discussion to delinquencies only.

The characteristics of loans and borrowers during the CARES period maintain a consistent pattern with the broader post-HAMP period, albeit with minor alterations. For instance, the *Credit Score* during CARES appears more significant in reducing for post-modification delinquency for the same 50 point increase (-2.68% versus -1.72%). A similar behavioural shift is observed for *Joint* borrowers, who are even less likely to enter delinquency post-modification. On the other hand, *Third Party Origination* mortgages are less likely to become delinquent. This counter-intuitive behaviour most likely highlights those accounts originated before the GFC that are approaching maturity and, due to financial struggle or externalities, might need a further modification to complete their mortgage repayment. All other loan- and borrower-level variables align with the post-HAMP interaction term or, if contrasting like *Judicial*, lack significance.

Interesting remarks are associated with variables related to mortgage modification types. For instance, the impacts of term extension is stronger during the period of CARES Act, yielding a decrease in delinquency probability post-modification by 2.7%. On the other hand, interest rate reduction is weaker during the same period, as a 25 percent reduction in interest rates yields a decrease in delinquency by 3.27%, compared with 6.78% during the post-HAMP. This corroborates that borrowers who seek modification and are granted one, while temporary payment suspension is also available with minimal documentation, are essentially mortgagors in financial distress pursuing a long-term solution rather than a short-term one, and substantially benefit from payment reductions. This reveals that servicers and lenders have effectively learnt to target modifications following the program cessation, offering the right amount of payment relief to avoid further delinquencies. It also reveals the ability to well screen these mortgagors from those who strategically apply for modifications and who could perhaps afford the mortgage they currently hold (Loewenstein and Njinju (2022) and Anderson et al. (2022). It would be anyway worthwhile to replicate this analysis once more data post-CARES is accumulated, to determine whether this interpretation holds true over a longer horizon.

A final remark pertains to the macroeconomic variables utilised within the model. The annual change in unemployment, lagged by two years, positively affects the likelihood of both delinquency and liquidation, whilst negatively influencing prepayments. This variable is economically and statistically significant, and its value remains relatively stable across the different models. The two-year lag is crucial in accurately capturing the liquidation behaviour, which typically transpires several months following a new transition into a delinquency status. The interest rate spread yields a positive influence on delinquency, liquidation, and prepayment alike. An increase in the spread prompts borrowers with the capacity to refinance to prepay in search of more favourable deals elsewhere (Green and Shoven (1983), Schwartz and Torous (1993), and Pavlov (2001)). Conversely, borrowers who have received a modification, and whose mortgage rate significantly exceeds the prevailing market rate, are also more likely to re-enter delinquency due to their inability to refinance, potentially resulting from their existing precarious situation (Keys et al. (2016)).

4.5 Conclusions

This chapter explored the outcomes of post-modification and its determining factors, considering a spectrum of loan-, borrower-, and modification-specific characteristics. Utilising a comprehensive dataset of Freddie Mac mortgages spanning two decades, we examine post-modification resolutions, encapsulating the entire cycle of the HAMP program, its subsequent phase-out, and the CARES Act period during the COVID-19 pandemic. Our analysis corroborates earlier findings that demonstrate the efficacy of payment reduction in maintaining current status following loan modification over the entire HAMP program. Specifically, interest rate reduction emerges as a successful tool in precluding post-modification transition to default, although less impactful in reducing foreclosures, whereas term extension has a reduced short-term impact, but it is more effective over a longer horizon.

Our study further reveals that payment relief retains its significance even after the termination of HAMP, once modification programs have been fully assimilated into the mortgage market, although the impact does not remain constant. Particularly, the effectiveness of interest rate reduction appears to have increased, while term extension shows a decline in keeping borrowers current in their payments. We also discover that the beneficial effect of timely modifications remains consistent regardless of the period under scrutiny, suggesting that lenders and servicers should vigilantly monitor portfolio dynamics to minimise unsuccessful modifications, as well-timed interventions drive successful post-modification resolutions .

We further investigate the borrower- and loan-level characteristics that affect post-modification resolutions. Factors such as credit score, loan-to-value ratio, joint borrowers, and refinance mortgages contribute to higher probabilities of positive outcomes. These factors, although generally aligned with previous literature, underscore a different sensitivity of GSE securitised mortgages and uncover that loans with similar characteristics are not assimilated to the overall subprime universe.

Lastly, by focusing on mortgages modified under the CARES Act, we manage to verify if lenders and servicers renegotiation practices are effective in targeting the right borrowers, or instead might not be able to distinguish between those that genuinely require a permanent modification from those that may act strategically. Thanks to the unique policy period offered by the CARES Act, where temporary payment relief were granted, we observe that borrowers' post-modification behaviour remains stable, highlighting that lenders and servicers practices have been well integrated into the market and are able to correctly target mortgagors in financial need.

Figure 4.1: Mortgage Modifications by State

The Graph displays the distribution of modified mortgages by States across the entire sample. The sample covers Single-Family residential mortgages originated from February 1999 to July 2022 and securitised by Freddie Mac. The figure displays all modified mortgages made available in Freddie Mac database.

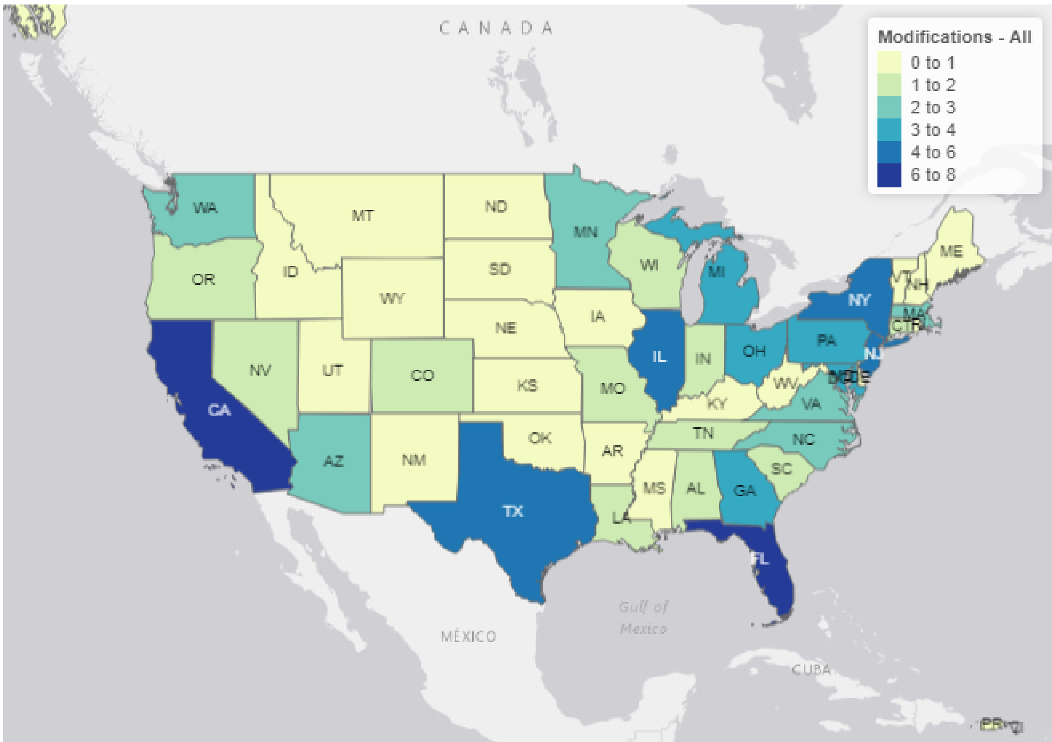
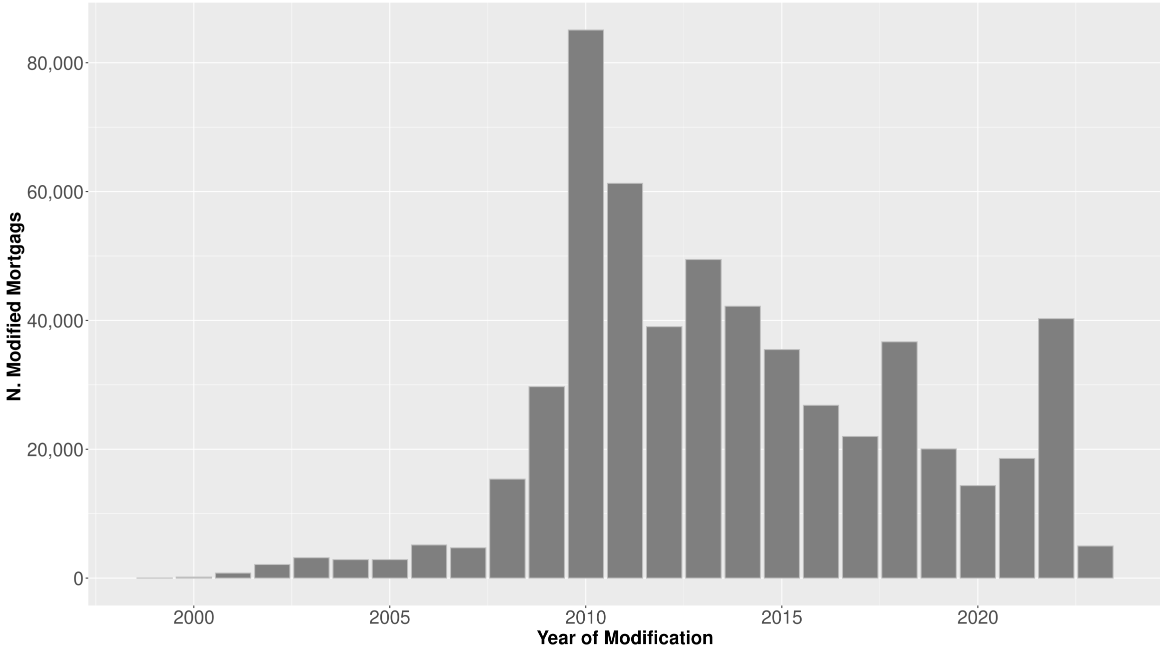
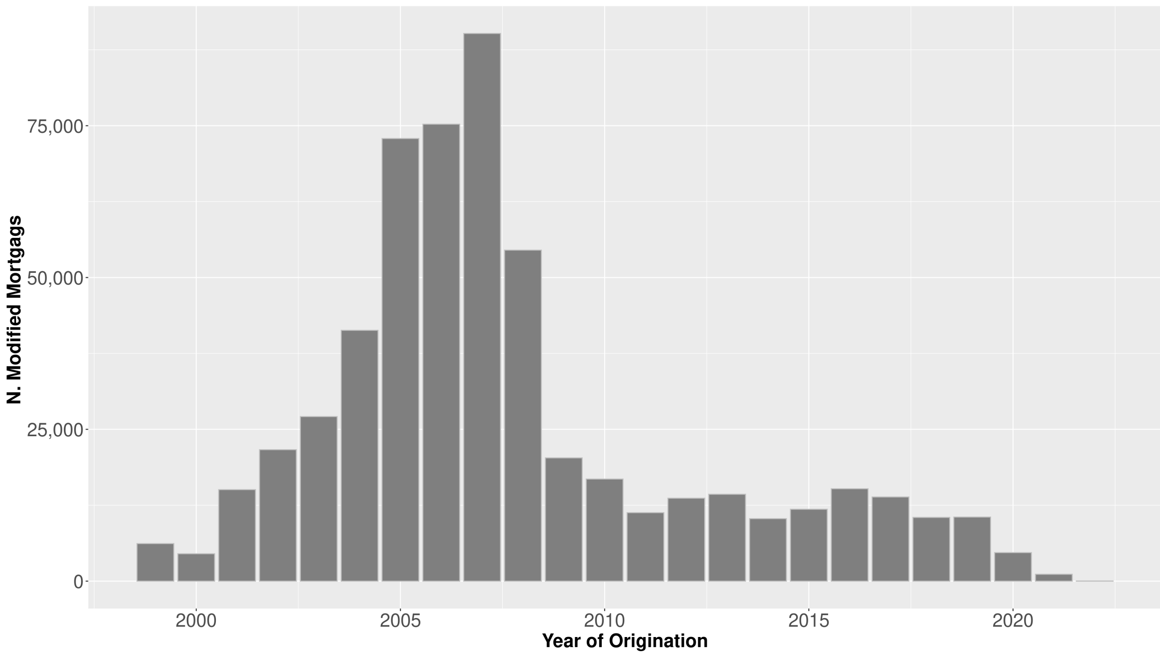


Figure 4.2: Mortgage Modifications by Year of Modification and Year of Origination

The Graph displays the number of modifications (a) by year of modification and (b) by year of origination.



(a)



(b)

Figure 4.3: Mortgage Modifications by Vintage

The Graph displays the share of renegotiation number by year of origination. The modification number is the number of times a mortgage contract has been successfully renegotiated.

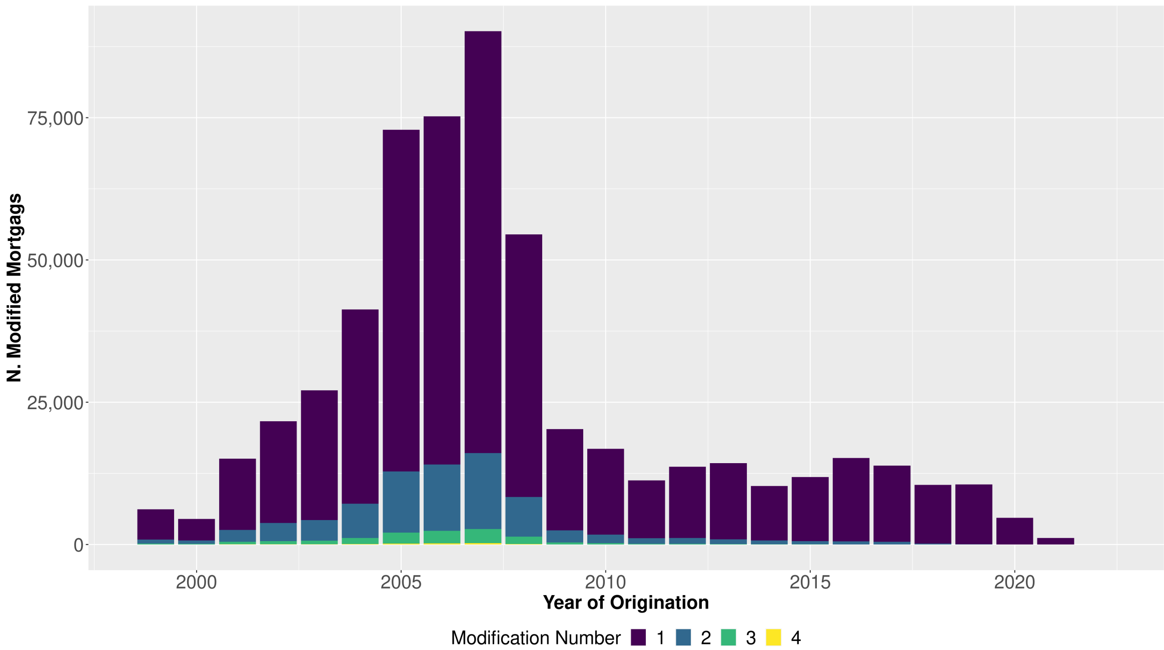
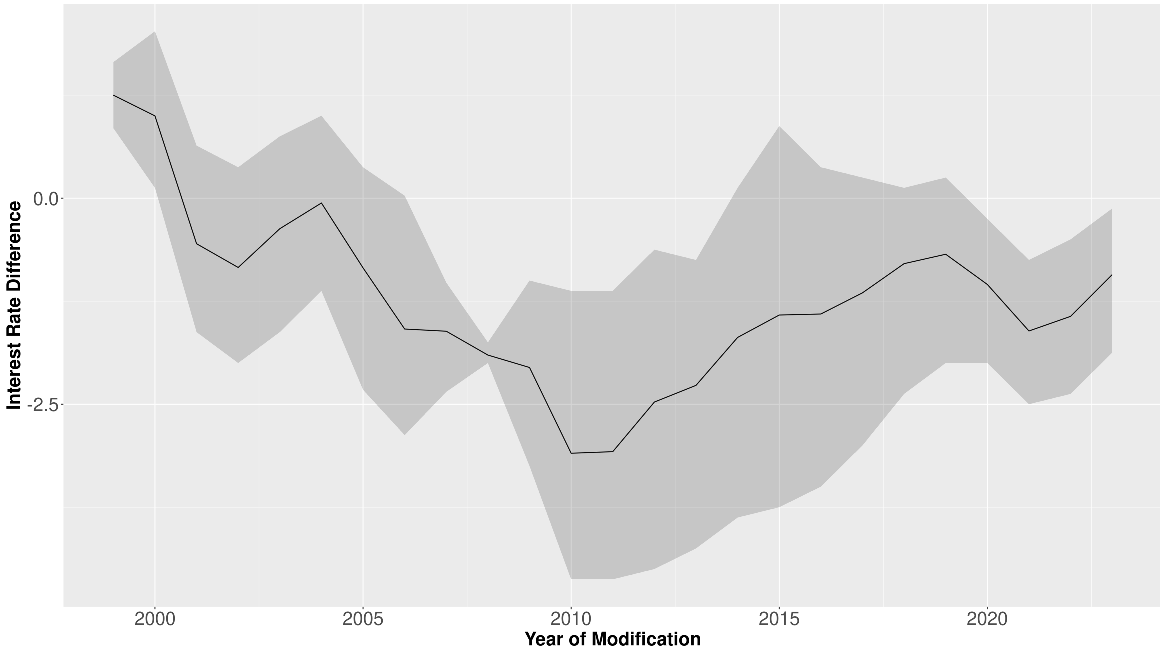
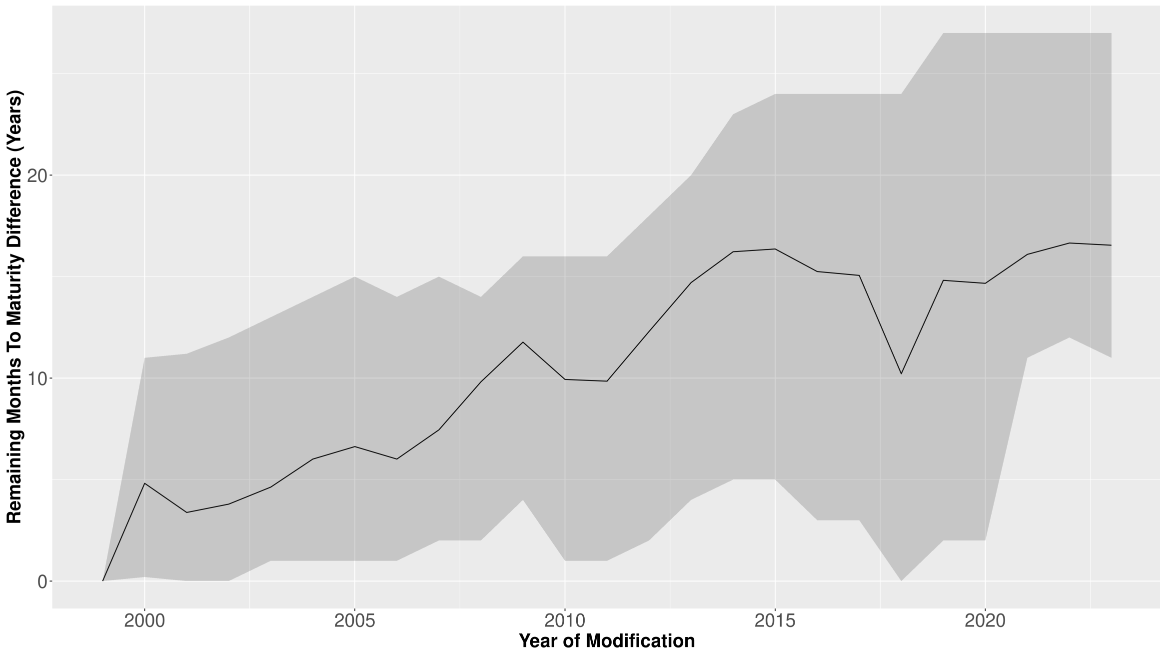


Figure 4.4: Interest Rate Change and Term Extension by Year of Modification

The Graph displays average interest rate change (a) and term extension (b) by year of modification. Interest rate change (term extensions) is calculated as the difference between interest rate (remaining months to maturity) following modification with the previous one. The shaded area delimits the 5^{th} and 95^{th} percentiles of the distribution.



(a)



(b)

Figure 4.5: Loan Termination by Year of Modification

The Graph displays the distribution of loan termination by year of modification. Loan termination is the final observable status for each loan in the portfolio. The possible termination statuses are: *REO/Foreclosure Sale*, *Prepaid/Matured*, *Modification*, *Reperforming* and *60+Delinquent*. *REO/Foreclosure* sale implies the selling of the property, either by the lender or third party. *Prepaid/Matured* is a voluntary pay-off, either because the borrower refinances elsewhere or because all the payments have been completed. *Reperforming* is the selling of reperforming loan operated by Freddie Mac. *60+Delinquent* represents the loan being in a delinquency status.

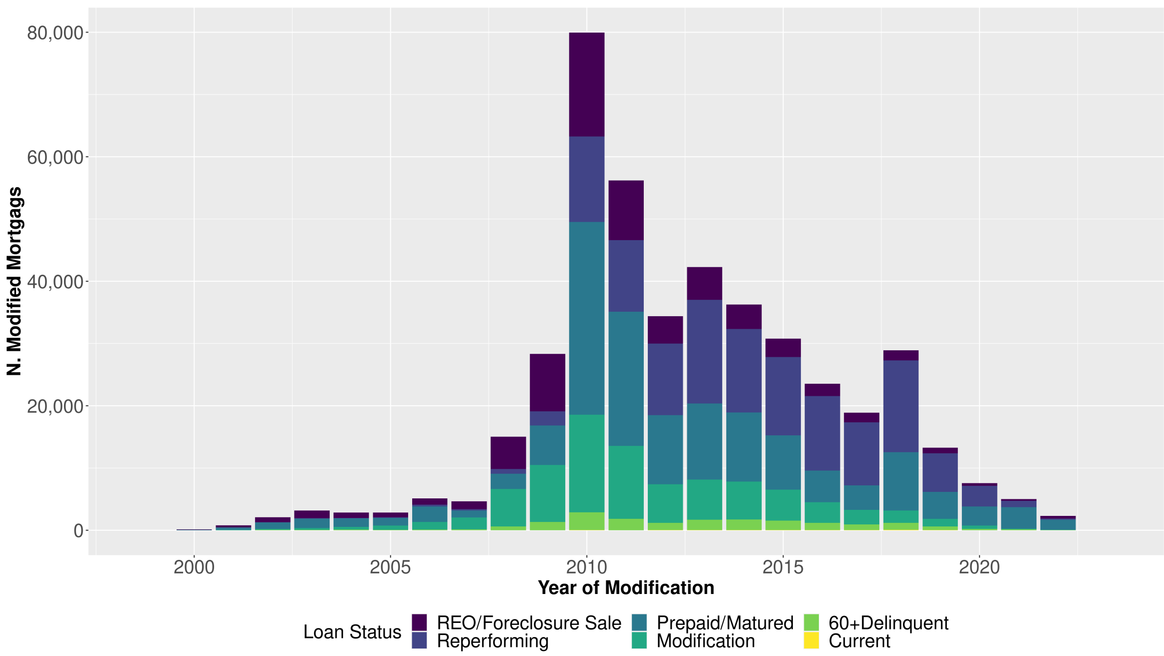


Table 4.1: Variables and Acronyms Definition

The table provides a summary of the explanatory variables used in the model estimation, as well as relevant acronyms used throughout the paper. For additional details, please refer to Federal Home Loan Mortgage Corporation (FHLMC) (2022).

Variable Name	Definition
Credit Score	Prepared by thirds parties, the variable summarises borrower's creditworthiness, hence its likelihood of timely repay future instalments. This is the score used to originate the mortgage. The variable ranges from a minimum of 300 to a maximum of 850.
Debt-to-Income	The sum of the borrower's monthly debt payments, including housing expenses that incorporate the mortgage payment, divided by the total monthly income used to underwrite the loan at time of origination. The variable ranges from a minimum of 0 (excluded) to a maximum of 65.
Loan-to-Value	The ratio obtained by dividing the original mortgage loan amount by the mortgaged property's appraised value at time of origination, or its purchase price. The variable ranges from a minimum of 1 to a maximum of 105.
Joint	It indicates that there is more than one borrower who is obligated to repay the mortgage secured by the mortgaged property.
Non Judicial	It flags those U.S. states where a lender is not obliged to go through the court system to initiate the foreclosure process of a home.
Recourse	It flags those U.S. jurisdictions where the lender, in the event of a foreclosure, can go after the borrower for any remaining balance left after the property is sold.
Single-family	It indicates that the property type backing the mortgage is a Single-Family house. Single-family houses are single-detached or standalone residential buildings designed to be occupied by a single family. It is not connected to other dwelling units. They differ from other property types in the sample like Manufactured House, Condominium, Co-op and Planned-Unit-Development
TPO	It indicates that, following the loan origination, the intermediary channel has not been specified nor reported by the lender. Alternative options include: Retail, Broker or Correspondent.
HAMP Flag	It flags if a mortgage is eligible for HAMP (Home Affordable Modification Program). The following criteria must be satisfied: the loan was originated before January 1^{st},2009; unpaid principal balance up to \$ 729,750; debt-to-income ratio has to be greater than 31%; current interest rate cannot be below 2%; the loan modification was modified from January 2009 until December 2016.
IR Change (Neg)	It is the percentage change. following modification, of mortgage interest rate. It is populated only when the change is negative.
Term Extension	Term increase (in years) following loan modification via extension of contractual maturity date.
Max Delinquency	Maximum number of months in arrears that the loan cumulated before being modified.
IR Spread	Difference between mortgage interest rate at origination and Freddie Mac 30-Year interest rate curve.
Ump_{12}^{lag2Yr}	1-year growth rate of State-level Unemployment, lagged by 2 years.
$PostHAMP$	Dummy indicator that separates those mortgages modified after the end of Home Affordable Modification Program (HAMP) period (December 2016).
$CARES$	Dummy indicator that separates those mortgages modified during Coronavirus Aid, Relief, and Economic Security Act (CARES Act) period (March 2020 to February 2021).

Table 4.2: Mortgage Sample Characteristics at Modification: Categorical

The Table reports percentage distribution of property and borrower types by year of modification: *Purpose*: Cash-out Refinance (C), No Cash-out Refinance (N), Purchase (P); Origination *Channel*: Broker (Brok), Correspondent (Corr), Retail (Ret), TPO Not Specified (TPO); *First time home buyer*; *Occupancy*: Investment (Inv), Primary Home(Pr), Second Home (Sec); *Number of Borrowers*: Single (S), Joint (J).

		Loan Purpose			Channel				First Time Buyer		Occupancy			N.Borrowers	
Year	N.Modifications	C	N	P	Brok	Corr	Ret	TPO	No	Yes	Inv	Pr	Sec	S	J
1999	2	0.00%	50.00%	50.00%	0.00%	0.00%	50.00%	50.00%	100.00%	0.00%	0.00%	100.00%	0.00%	50.00%	50.00%
2000	153	20.92%	32.03%	47.06%	0.00%	0.00%	32.68%	67.32%	81.05%	18.95%	0.65%	98.04%	1.31%	55.56%	44.44%
2001	776	19.97%	29.90%	50.13%	0.00%	0.00%	37.24%	62.76%	84.92%	15.08%	2.19%	97.29%	0.52%	51.93%	48.07%
2002	2,103	19.73%	33.71%	46.55%	0.10%	0.00%	34.47%	65.43%	85.40%	14.60%	1.28%	98.10%	0.62%	51.21%	48.79%
2003	3,162	22.52%	35.93%	41.56%	0.00%	0.03%	32.26%	67.71%	85.90%	14.10%	1.17%	97.88%	0.95%	53.00%	47.00%
2004	2,863	25.22%	36.57%	38.21%	0.00%	0.03%	31.23%	68.74%	87.50%	12.50%	1.50%	97.73%	0.77%	53.86%	46.14%
2005	2,864	29.92%	38.13%	31.95%	0.00%	0.00%	32.05%	67.95%	89.66%	10.34%	1.57%	97.59%	0.84%	52.27%	47.73%
2006	5,146	30.02%	39.33%	30.65%	0.02%	0.02%	32.20%	67.76%	91.97%	8.03%	3.52%	95.24%	1.24%	51.32%	48.68%
2007	4,704	34.40%	35.33%	30.27%	0.00%	0.02%	35.16%	64.82%	90.60%	9.40%	1.19%	98.09%	0.72%	52.25%	47.75%
2008	15,362	38.63%	27.44%	33.93%	0.02%	0.00%	33.95%	66.03%	89.25%	10.75%	1.33%	97.61%	1.05%	55.16%	44.84%
2009	29,717	42.34%	25.41%	32.25%	0.50%	0.34%	35.76%	63.39%	89.87%	10.13%	2.03%	96.68%	1.29%	52.63%	47.37%
2010	85,078	44.90%	25.41%	29.69%	2.24%	2.45%	35.68%	59.63%	90.61%	9.39%	1.11%	97.68%	1.21%	52.34%	47.66%
2011	61,274	46.77%	25.77%	27.46%	2.90%	2.89%	39.39%	54.82%	91.22%	8.78%	1.08%	97.59%	1.33%	52.08%	47.92%
2012	39,028	45.39%	27.65%	26.96%	2.78%	3.46%	41.22%	52.54%	91.39%	8.61%	1.60%	96.91%	1.49%	52.36%	47.64%
2013	49,450	43.37%	30.45%	26.19%	3.42%	4.69%	42.63%	49.27%	91.32%	8.68%	2.65%	95.37%	1.99%	52.64%	47.36%
2014	42,199	40.49%	35.31%	24.20%	3.23%	5.38%	46.26%	45.12%	91.86%	8.14%	3.32%	94.85%	1.83%	52.71%	47.29%
2015	35,474	37.05%	38.65%	24.30%	3.66%	6.66%	50.33%	39.34%	91.52%	8.48%	3.79%	94.21%	2.00%	55.33%	44.67%
2016	26,818	33.95%	41.27%	24.78%	4.02%	8.59%	53.12%	34.28%	91.04%	8.96%	3.36%	95.12%	1.52%	56.13%	43.87%
2017	21,985	31.66%	41.82%	26.52%	4.54%	11.88%	53.67%	29.91%	90.03%	9.97%	3.58%	94.67%	1.75%	57.21%	42.79%
2018	36,678	28.64%	37.71%	33.64%	6.61%	16.36%	57.26%	19.77%	85.53%	14.47%	3.88%	94.16%	1.96%	58.21%	41.79%
2019	20,048	27.08%	37.67%	35.26%	6.26%	18.69%	57.35%	17.70%	84.00%	16.00%	3.58%	94.59%	1.83%	61.73%	38.27%
2020	14,358	25.67%	34.04%	40.30%	7.91%	22.11%	56.96%	13.02%	79.88%	20.12%	3.61%	94.77%	1.62%	63.52%	36.48%
2021	18,572	23.01%	32.03%	44.96%	10.24%	28.26%	55.42%	6.07%	77.86%	22.14%	5.25%	92.84%	1.91%	61.36%	38.64%
2022	40,276	23.66%	31.26%	45.07%	10.67%	30.04%	54.83%	4.45%	77.01%	22.99%	6.83%	91.17%	2.00%	66.00%	34.00%
2023	4,980	24.98%	28.69%	46.33%	10.88%	29.62%	55.26%	4.24%	75.08%	24.92%	4.36%	94.10%	1.55%	67.27%	32.73%

Table 4.3: Mortgage Sample Characteristics at Modification: Continuous

The Table reports 5^{th} quantile, mean, standard deviation and 95^{th} quantile of *Credit Score*, *Debt-to-Income*, *Interest rate* and *Loan-to-Value* by year of modification. *Credit Score* is borrower's Credit Score at origination. *Debt-to-Income* is the sum of borrower's monthly debt payments, including housing expenses that incorporate mortgage payment, divided by total monthly income used for underwriting. *Interest rate* is the contractual interest rate at origination. *Original Loan-to-Value* is the ratio between $Balance$ and $PropertyPrice_t$ at origination. *Updated Loan-to-Value* is the ratio between outstanding $Balance_t$ and $PropertyPrice_t$, which is derived from State-level House Price Index at time t.

	Credit Score				Debt-to-Income				Interest Rate				Original Loan-to-Value				Updated Loan-to-Value			
Year	q5	Mean	Sd	q95	q5	Mean	Sd	q95	q5	Mean	Sd	q95	q5	Mean	Sd	q95	q5	Mean	Sd	q95
1999	549.3	597.0	75.0	644.7	29.6	35.0	8.5	40.4	6.8	7.1	0.5	7.5	75.1	84.5	14.8	94.0	78.0	85.7	12.1	93.3
2000	539.5	631.9	55.7	727.5	19.0	34.8	9.5	50.5	6.8	7.7	0.7	8.8	60.6	84.1	11.6	95.8	59.1	83.3	12.9	100.4
2001	545.8	629.4	49.9	712.2	22.0	37.1	9.6	53.0	6.9	8.1	0.9	9.9	63.0	84.2	11.6	97.0	58.6	80.6	13.1	97.1
2002	552.0	634.8	49.8	717.9	20.0	36.9	10.0	52.0	6.8	7.9	0.9	9.5	65.0	84.9	11.1	95.0	53.9	78.6	15.0	96.6
2003	548.0	634.5	52.4	723.0	20.0	37.4	10.0	53.0	6.6	7.6	0.8	9.0	65.0	84.5	11.1	95.0	51.5	76.8	14.5	95.7
2004	555.0	638.2	50.7	727.0	19.0	37.1	10.2	53.0	6.0	7.3	0.8	8.8	65.0	83.9	11.2	95.0	46.0	72.5	15.2	93.1
2005	560.0	640.6	52.2	728.0	19.0	36.6	10.0	52.0	5.5	6.9	0.9	8.5	61.0	82.3	11.5	95.0	41.6	68.3	15.2	90.3
2006	579.0	655.4	54.1	756.0	17.0	36.3	11.4	55.0	5.3	6.4	0.9	8.1	57.0	80.3	12.4	95.0	40.0	66.6	15.1	90.4
2007	576.0	646.1	48.7	731.3	19.0	37.4	10.7	55.0	5.4	6.4	0.8	8.0	57.0	80.1	12.3	95.0	42.7	71.5	16.7	98.0
2008	582.0	651.8	48.6	738.0	20.0	39.3	11.0	58.0	5.4	6.4	0.7	7.6	57.0	80.0	12.5	97.0	48.8	86.7	23.2	125.3
2009	588.0	660.9	50.1	751.0	21.0	40.1	11.1	59.0	5.4	6.3	0.6	7.4	57.0	79.8	12.4	100.0	55.5	99.2	27.5	148.0
2010	597.0	680.6	54.0	773.0	23.0	42.0	10.9	60.0	5.4	6.3	0.6	7.3	55.0	77.7	12.4	95.0	54.5	97.8	27.6	145.1
2011	599.0	682.3	54.5	774.0	22.0	41.3	11.0	60.0	5.4	6.2	0.6	7.1	53.0	76.7	12.8	95.0	55.2	101.8	30.6	155.6
2012	598.0	682.9	55.2	775.0	22.0	40.9	11.0	60.0	5.3	6.2	0.6	7.1	53.0	77.1	13.2	95.0	54.1	96.7	27.9	145.4
2013	597.0	682.9	54.8	775.0	21.0	40.3	11.1	59.0	5.0	6.1	0.7	7.1	54.0	78.4	13.7	100.0	48.4	85.6	23.8	126.1
2014	595.0	680.6	55.7	773.0	21.0	39.6	11.2	58.0	4.8	6.0	0.8	7.1	52.0	78.4	15.1	100.0	38.7	76.5	23.1	115.3
2015	590.0	680.2	57.4	775.0	20.0	38.9	11.3	58.0	4.3	5.8	0.9	7.1	49.0	78.2	16.8	102.0	31.0	70.3	24.4	112.3
2016	589.0	680.0	57.6	775.0	20.0	39.1	11.1	58.0	4.0	5.7	1.0	7.0	50.0	79.4	17.5	106.1	29.5	67.8	24.1	109.5
2017	589.0	681.0	57.5	776.0	20.0	38.7	10.8	56.0	3.8	5.5	1.0	7.0	50.0	79.6	17.3	106.0	27.8	63.1	22.1	99.2
2018	595.0	688.7	57.4	782.0	21.0	38.7	9.8	55.0	3.6	5.1	1.1	6.9	50.0	80.5	17.7	107.0	26.1	61.3	21.4	93.7
2019	595.0	686.2	56.5	779.0	21.0	38.4	9.6	53.0	3.6	5.0	1.1	6.9	50.0	80.1	17.4	104.0	24.8	59.1	21.0	91.4
2020	604.0	691.1	54.6	782.0	22.0	38.6	9.0	50.0	3.6	4.9	1.0	6.8	50.0	80.7	16.9	101.0	25.1	58.1	20.1	88.4
2021	622.0	706.6	53.7	791.0	23.0	39.0	8.3	50.0	3.5	4.6	0.9	6.4	50.0	81.0	16.6	98.0	21.8	53.2	18.1	79.5
2022	627.0	709.6	52.1	792.0	23.0	38.8	8.4	50.0	3.3	4.5	0.9	6.1	48.0	79.1	16.8	97.0	20.6	49.6	16.9	75.7
2023	623.0	701.6	51.9	786.0	23.0	38.2	8.2	49.0	2.9	4.3	1.0	6.1	49.0	79.2	16.3	97.0	21.7	52.9	18.3	81.9

Table 4.4: Modification Types by Year of Modification

The Table shows the distribution of renegotiation types by year of modification. *N.Modifications* is the number of modifications realised in the year considered. *Bal>0* is the increase in balance due to the charge of arrears payments to the loan outstanding amount; *Term >0* is the extension of loan term; *IR<0* is the decrease in contractual interest rate; *IR>0* is the increase in contractual interest rate. Mortgage renegotiations can include these changes either on a stand-alone basis or instead as a combination, as displayed in the remaining columns.

Year	N.Modifications	Bal>0	Term>0	IR<0	IR>0	Bal>0-Term>0	IR<0-Bal>0	IR>0-Bal>0	IR<0-Term>0	IR>0-Term>0	IR<0-Bal>0-Term>0	IR>0-Bal>0-Term>0
1999	2	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	100.00%
2000	153	0.00%	0.00%	0.00%	0.00%	9.15%	0.00%	0.00%	0.00%	0.00%	7.84%	83.01%
2001	776	0.90%	0.13%	0.00%	0.13%	37.11%	0.90%	0.26%	1.29%	0.26%	42.53%	16.49%
2002	2,103	8.75%	0.38%	0.05%	0.00%	40.51%	0.71%	0.24%	0.57%	0.00%	38.04%	10.41%
2003	3,162	27.07%	0.35%	0.00%	0.00%	46.20%	0.35%	3.54%	0.13%	0.06%	11.64%	10.37%
2004	2,863	53.51%	0.24%	0.00%	0.00%	28.96%	0.14%	5.17%	0.03%	0.10%	4.09%	7.16%
2005	2,864	70.08%	0.10%	0.00%	0.00%	27.90%	0.17%	0.10%	0.00%	0.00%	1.01%	0.28%
2006	5,146	71.10%	0.12%	0.00%	0.00%	28.12%	0.02%	0.02%	0.02%	0.00%	0.29%	0.06%
2007	4,704	62.27%	0.11%	0.00%	0.00%	37.10%	0.00%	0.00%	0.00%	0.00%	0.23%	0.02%
2008	15,362	40.98%	0.19%	0.00%	0.00%	31.72%	0.04%	0.02%	0.05%	0.00%	26.79%	0.03%
2009	29,717	10.54%	0.20%	0.26%	0.00%	31.06%	3.15%	0.00%	0.76%	0.01%	53.81%	0.05%
2010	85,078	3.60%	0.15%	2.09%	0.00%	13.41%	24.08%	0.00%	2.46%	0.00%	54.03%	0.04%
2011	61,274	5.34%	0.17%	1.85%	0.00%	16.76%	15.92%	0.01%	2.26%	0.00%	57.47%	0.09%
2012	39,028	1.32%	0.10%	0.89%	0.00%	7.50%	12.83%	0.00%	1.27%	0.05%	72.91%	3.07%
2013	49,450	0.03%	0.10%	0.47%	0.01%	9.36%	8.46%	0.00%	1.27%	0.07%	76.32%	3.86%
2014	42,199	0.02%	0.41%	0.41%	0.01%	25.54%	4.32%	0.00%	0.94%	0.16%	60.32%	7.82%
2015	35,474	0.03%	1.01%	0.32%	0.02%	46.17%	2.21%	0.01%	0.72%	0.21%	39.98%	9.23%
2016	26,818	0.10%	1.18%	0.21%	0.02%	47.75%	1.80%	0.01%	0.88%	0.28%	41.22%	6.48%
2017	21,985	0.15%	1.37%	0.12%	0.03%	54.81%	0.84%	0.00%	1.04%	0.27%	35.42%	5.88%
2018	36,678	0.34%	19.96%	0.05%	0.01%	59.62%	0.07%	0.00%	0.40%	0.24%	17.27%	1.86%
2019	20,048	0.05%	7.34%	0.03%	0.01%	80.65%	0.02%	0.01%	0.20%	0.15%	10.37%	1.11%
2020	14,358	0.43%	3.38%	0.03%	0.00%	69.85%	0.04%	0.00%	0.17%	0.00%	23.96%	0.47%
2021	18,572	0.51%	2.11%	0.02%	0.00%	69.98%	0.01%	0.00%	0.14%	0.01%	26.33%	0.05%
2022	40,276	0.01%	0.46%	0.00%	0.00%	31.65%	0.01%	0.00%	0.31%	0.00%	67.52%	0.03%
2023	4,980	0.04%	0.76%	0.00%	0.00%	91.29%	0.00%	0.00%	0.08%	0.00%	7.73%	0.10%

Table 4.5: Modification Types by Number of Renegotiations

The Table shows the distribution of modification types by number of renegotiations. *Bal>0* is the increase in balance due to the charge of arrears payments to the loan outstanding amount; *Term >0* is the extension of loan term; *IR<0* is the decrease in contractual interest rate; *IR>0* is the increase in contractual interest rate. Mortgage renegotiations can include these changes either on a stand-alone basis or instead as a combination, as displayed in the remaining rows.

	Renegotiation Number			
Modification Type	1	2	3	4
Bal>0	5.57%	1.39%	0.28%	0.10%
Term>0	2.15%	1.34%	1.51%	2.03%
IR<0	0.80%	0.17%	0.03%	0.00%
IR>0	0.00%	0.02%	0.01%	0.10%
Bal>0-Term>0	31.97%	32.21%	39.62%	38.08%
IR<0-Bal>0	8.28%	4.89%	3.71%	2.23%
IR>0-Bal>0	0.06%	0.02%	0.02%	0.00%
IR<0-Term>0	1.22%	0.58%	0.60%	0.39%
IR>0-Term>0.	0.01%	0.53%	0.29%	0.29%
IR<0-Bal>0-Term>0	49.06%	43.68%	43.72%	50.68%
IR>0-Bal>0-Term>0	0.70%	15.09%	10.12%	6.01%
Total	482,461	67,745	11,832	1,032
Perc. Modifications	85.68%	12.03%	2.10%	0.18%

Table 4.6: Determinants of Mortgage Post-Modification Outcomes: Marginal Effects

The Table shows average marginal effects of explanatory variables on the different outcomes of multinomial logit regression. The baseline outcome is *Current*, and it is not displayed being the reference category. The outcomes reported are: $60 +$ *Delinquent*, *Prepaid/Matured* and *Liquidation*. Standard errors of marginal effects are calculated using the delta method and are reported in parentheses. *Credit Score* is borrower's Credit Score at origination. *Debt-to-Income* is the sum of borrower's monthly debt payments, including housing expenses that incorporate mortgage payment, divided by total monthly income used for underwriting. *Joint* captures loans with more than one borrower. *Loan-to-Value* is the ratio between $Balance_t$ and $PropertyPrice_t$at origination. *Judicial* differentiate Judicial from Non-judicial states; *Non Recourse* differentiate Recourse States from Non-recourse states; *Not Single-family* distinguished Single-Family from other property types. *TPO* catches mortgages originated by Third Parties; *Purchase* separates Purchase from Refinance loan purpose; *HAMP Flag* absorbs the effect of mortgages eligible under HAMP program. *IR Change (Neg)* is the percentage change of mortgage interest rate before and after modification; it is populated only when it takes negative values. *Term Extension* is the number of additional years added to mortgage maturity date following modification. *Max Delinquency* is the maximum number of months in arrears cumulated by the borrower before being modified. *IR Spread* is the difference between mortgage interest rate at origination and Freddie Mac 30-Year interest rate curve. Ump_{12}^{lag2Yr} is the 1-year growth rate of State-level Unemployment, lagged by 2 years. ***, **, * denote statistical significance at the 1%, 5% and 10% levels respectively.

Variable	Prepaid/Matured	60+Delinquent	Liquidation
Credit Score	0.0000145***	-0.0004979***	-0.00000351***
	(0.000000237)	(0.00000704)	(0.000000175)
Debt-to-Income	0.0000087***	0.000125***	0.0000055***
	(0.000001)	(0.0000312)	(0.000000759)
Loan-to-Value	-0.0000409***	0.0005127***	0.0000386***
	(0.00000093)	(0.0000285)	(0.000000713)
Joint	0.0008148***	-0.0215008***	-0.0004402***
	(0.0000252)	(0.0007643)	(0.000019)
Judicial	-0.0009167***	0.0185514***	-0.0002184***
	(0.0000274)	(0.0008461)	(0.0000211)
Non Recourse	0.0007101***	-0.0175993***	0.000293***
	(0.0000323)	(0.0009525)	(0.000026)
Not Single-Family	0.0007238***	-0.0104858***	0.0000802***
	(0.0000335)	(0.0009653)	(0.0000247)
TPO	-0.0005782***	0.0151954***	0.0006785***
	(0.0000257)	(0.0008177)	(0.0000206)
Purchase	0.000674***	0.0184084***	0.000241***
	(0.0000311)	(0.0009254)	(0.0000223)
HAMP Flag	-0.0007493***	-0.0131849***	-0.0011174***
	(0.0000283)	(0.0008949)	(0.0000233)
IR Change (Neg)	0.0000698***	0.0022798***	0.0000142***
	(0.000000575)	(0.0000169)	(0.00000041)
Term Extension	-0.0001037***	-0.0029197***	-0.0000803***
	(0.00000161)	(0.000045)	(0.00000124)
Max Delinquency	-0.0000886***	0.0025642***	0.0000354***
	(0.00000214)	(0.0000419)	(0.00000136)
IR Spread	0.0003343***	0.0234812***	0.0006048***
	(0.0000143)	(0.0003387)	(0.0000101)
Ump_{12}^{lag2Yr}	-0.0004487***	0.0079902***	0.0002673***
	(0.0000109)	(0.000123)	(0.0000044)
Log-likelihood	-13976211		
Wald Chi-Sq	90274.94		
Pseudo-R^2	0.0444		
N. Observations	28,869,343		
N. Mortgages	481,703		

Table 4.7: Determinants of Mortgage Post-Modification Outcomes: Relative Risk Ratios

The Table shows relative risk ratios of explanatory variables on the different outcomes of multinomial logit regression. The baseline outcome is *Current*, and it is not displayed being the reference category. The outcomes reported are: $60 + Delinquent$, *Prepaid/Matured* and *Liquidation.* Standard errors of marginal effects are calculated using the delta method and are reported in parentheses. *Credit Score* is borrower's Credit Score at origination. *Debt-to-Income* is the sum of borrower's monthly debt payments, including housing expenses that incorporate mortgage payment, divided by total monthly income used for underwriting. *Joint* captures loans with more than one borrower. *Loan-to-Value* is the ratio between $Balance_t$ and $PropertyPrice_t$at origination. *Judicial* differentiate Judicial from Non-judicial states; *Non Recourse* differentiate Recourse States from Non-recourse states; *Not Single-family* distinguished Single-Family from other property types. *TPO* catches mortgages originated by Third Parties; *Purchase* separates Purchase from Refinance loan purpose; *HAMP Flag* absorbs the effect of mortgages eligible under HAMP program. *IR Change (Neg)* is the percentage change of mortgage interest rate before and after modification; it is populated only when it takes negative values. *Term Extension* is the number of additional years added to mortgage maturity date following modification. *Max Delinquency* is the maximum number of months in arrears cumulated by the borrower before being modified. *IR Spread* is the difference between mortgage interest rate at origination and Freddie Mac 30-Year interest rate curve. Ump_{12}^{lag2Yr} is the 1-year growth rate of State-level Unemployment, lagged by 2 years. ***, **, * denote statistical significance at the 1%, 5% and 10% levels respectively.

Variable	Prepaid/Matured	60+Delinquent	Liquidation
Credit Score	1.002246***	0.9963628***	0.9978368***
	(0.0000473)	(0.0000516)	(0.0000762)
Debt-to-Income	1.001919***	1.000939***	1.002442***
	(0.0002013)	(0.0002294)	(0.0003307)
Loan-to-Value	0.9925516***	1.003778***	1.016565***
	(0.0001843)	(0.0002107)	(0.0003055)
Joint	1.142672***	0.8537239***	0.8088222***
	(0.005675)	(0.0048406)	(0.0067803)
Judicial	0.8509264***	1.143825***	0.9398902***
	(0.0047431)	(0.0070739)	(0.0086482)
Non Recourse	1.121698***	0.8775377***	1.093818***
	(0.0067386)	(0.006406)	(0.0115115)
Not Single-Family	1.133609***	0.9258087***	1.017456***
	(0.0069584)	(0.006769)	(0.0106852)
TPO	0.9090399***	1.118195***	1.348475***
	(0.0046951)	(0.0067038)	(0.0120953)
Purchase	1.168948***	1.143615***	1.133289***
	(0.0068436)	(0.0075273)	(0.0106649)
HAMP Flag	0.8448972***	0.9055901***	0.6297223***
	(0.0047366)	(0.0059175)	(0.0059472)
IR Change (Neg)	1.017196***	1.017005***	1.00937***
	(0.0001109)	(0.0001287)	(0.0001832)
Term Extension	0.9755273***	0.9785262***	0.9634669***
	(0.0003147)	(0.0003232)	(0.0005045)
Max Delinquency	0.9857943***	1.01895***	1.018336***
	(0.0004232)	(0.0003141)	(0.0005907)
IR Spread	1.104096***	1.189886***	1.325889***
	(0.0031822)	(0.0029438)	(0.005529)
Ump_{12}^{lag2Yr}	0.9240348***	1.060252***	1.127774***
	(0.0020145)	(0.0009608)	(0.0020245)
Log-likelihood	-13976211		
Wald Chi-Sq	90274.94		
Pseudo-R^2	0.0444		
N. Observations	28,869,343		
N. Mortgages	481,703		

Table 4.8: Determinants of Mortgage Post-Modification Outcomes by HAMP Period: Marginal Effects

The Table shows average marginal effects of explanatory variables on the different outcomes of multinomial logit regression. The baseline outcome is *Current*, and it is not displayed being the reference category. The outcomes reported are: $60 + Delinquent$, *Prepaid/Matured* and *Liquidation*. Standard errors of marginal effects are calculated using the delta method and are reported in parentheses. *Credit Score* is borrower's Credit Score at origination. *Debt-to-Income* is the sum of borrower's monthly debt payments, including housing expenses that incorporate mortgage payment, divided by total monthly income used for underwriting. *Joint* captures loans with more than one borrower. *Loan-to-Value* is the ratio between $Balance_t$ and $PropertyPrice_t$at origination. *Judicial* differentiate Judicial from Non-judicial states; *Non Recourse* differentiate Recourse States from Non-recourse states; *Not Single-family* distinguished Single-Family from other property types. TPO catches mortgages originated by Third Parties; *Purchase* separates Purchase from Refinance loan purpose; *HAMP Flag* absorbs the effect of mortgages eligible under HAMP program. *IR Change (Neg)* is the percentage change of mortgage interest rate before and after modification; it is populated only when it takes negative values. *Term Extension* is the number of additional years added to mortgage maturity date following modification. *Max Delinquency* is the maximum number of months in arrears cumulated by the borrower before being modified. *IR Spread* is the difference between mortgage interest rate at origination and Freddie Mac 30-Year interest rate curve. Ump_{12}^{lag2Yr} is the 1-year growth rate of State-level Unemployment, lagged by 2 years. The $PostHAMP$ period spans over the years following lift of HAMP program (from 2017 onwards) and is activated using a dummy variable for mortgages modified in this period. The sample includes mortgages originated from 1999 to 2022 and observed from 1999 to 2023. ***, **, * denote statistical significance at the 1%, 5% and 10% levels respectively.

Variable	Prepaid/Matured	60+Delinquent	Liquidation
Credit Score	0.0000137***	-0.0005154***	-0.00000329***
	(0.000000248)	(0.00000775)	(0.000000202)
Debt-to-Income	0.0000102***	0.0001654***	0.0000107***
	(0.00000107)	(0.0000346)	(0.000000858)
Loan-to-Value	-0.0000454***	0.0005473***	0.0000453***
	(0.000001)	(0.0000329)	(0.00000086)
Joint	0.0008874***	-0.0197309***	-0.0005451***
	(0.0000261)	(0.0008394)	(0.0000219)
Judicial	-0.0009112***	0.0236569***	-0.000189***
	(0.0000286)	(0.0009368)	(0.0000243)
Non Recourse	0.0006598***	-0.0187861***	0.0002958***
	(0.0000329)	(0.0010311)	(0.0000296)
Not Single-Family	0.0004213***	-0.0078841***	0.0002357***
	(0.0000349)	(0.001099)	(0.0000295)
TPO	-0.0002697***	0.014414***	0.0005202***
	(0.0000262)	(0.0008628)	(0.0000231)
Purchase	0.000506***	0.0175583***	0.0003649***
	(0.0000327)	(0.0010394)	(0.0000264)
HAMP Flag	-0.0002968***	-0.0160785***	-0.0015022***
	(0.000029)	(0.0009698)	(0.0000262)
IR Change (Neg)	0.0000667***	0.0022566***	0.0000218***
	(0.000000588)	(0.0000183)	(0.000000481)
Term Extension	-0.0001116***	-0.0032409***	-0.0000855***
	(0.00000173)	(0.0000513)	(0.00000144)
Max Delinquency	-0.0000967***	0.0025957***	0.0000426***
	(0.00000227)	(0.0000472)	(0.00000108)
Post-HAMP*Credit Score	0.0000103***	-0.0003793***	-0.0000000631
	(0.000000497)	(0.000016)	(0.000000345)
Post-HAMP*Debt-to-Income	-0.0000117***	0.0001145	-0.00000249
	(0.00000205)	(0.0000722)	(0.00000157)
Post-HAMP*Loan-to-Value	-0.0000137***	0.000461***	0.0000119***
	(0.0000017)	(0.000057)	(0.00000125)
Post-HAMP*Joint	0.0005175***	-0.0334334***	-0.0002532***
	(0.0000541)	(0.0018024)	(0.0000399)
Post-HAMP*Judicial	-0.0005505***	-0.0094572***	-0.0001449***
	(0.0000567)	(0.0019007)	(0.0000424)
Post-HAMP*Non Recourse	0.000741***	-0.0074398***	0.0000644
	(0.000077)	(0.0023654)	(0.0000543)

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Table 4.8

Variable	Prepaid/Matured	60+Delinquent	Liquidation
Post-HAMP*Not Single-Family	0.0011359***	-0.0206984***	-0.0001748***
	(0.0000673)	(0.0019743)	(0.0000416)
Post-HAMP*TPO	-0.0018412***	0.0096574***	-0.000213***
	(0.0000829)	(0.0025913)	(0.0000535)
Post-HAMP*Purchase	0.0004208***	0.0243327***	0.0001651***
	(0.0000613)	(0.0020616)	(0.0000453)
Post-HAMP*HAMP Flag	-0.0035194***	0.0423186***	-0.0000145***
	(0.0000969)	(0.0028995)	(0.0000597)
Post-HAMP*IR Change (Neg)	0.0000605***	0.0024938***	-0.00000732***
	(0.00000228)	(0.0000581)	(0.00000151)
Post-HAMP*Term Extension	-0.0000573***	-0.0013215***	-0.0000118***
	(0.00000325)	(0.0001017)	(0.00000225)
Post-HAMP*Max Delinquency	-0.0000319***	0.0025407***	0.0000178***
	(0.00000419)	(0.000096)	(0.00000199)
IR Spread	0.0005136***	0.0229129***	0.0004739***
	(0.0000145)	(0.0003469)	(0.0000105)
Ump_{12}^{lag2Yr}	-0.0004824***	0.0075827***	0.0002897***
	(0.0000111)	(0.0001257)	(0.00000456)
Log-likelihood	-13957737		
Wald Chi-Sq	101335.82		
Pseudo-R^2	0.0457		
N. Observations	28,869,343		
N. Mortgages	481,703		

Table 4.9: Determinants of Mortgage Post-Modification Outcomes by HAMP Period: Relative Risk Ratios

The Table shows relative risk ratios of explanatory variables on the different outcomes of multinomial logit regression. The baseline outcome is *Current*, and it is not displayed being the reference category. The outcomes reported are: $60 + Delinquent$, *Prepaid/Matured* and *Liquidation*. Standard errors of marginal effects are calculated using the delta method and are reported in parentheses. *Credit Score* is borrower's Credit Score at origination. *Debt-to-Income* is the sum of borrower's monthly debt payments, including housing expenses that incorporate mortgage payment, divided by total monthly income used for underwriting. *Joint* captures loans with more than one borrower. *Loan-to-Value* is the ratio between $Balance_t$ and $PropertyPrice_t$at origination. *Judicial* differentiate Judicial from Non-judicial states; *Non Recourse* differentiate Recourse States from Non-recourse states; *Not Single-family* distinguished Single-Family from other property types. TPO catches mortgages originated by Third Parties; *Purchase* separates Purchase from Refinance loan purpose; *HAMP Flag* absorbs the effect of mortgages eligible under HAMP program. *IR Change (Neg)* is the percentage change of mortgage interest rate before and after modification; it is populated only when it takes negative values. *Term Extension* is the number of additional years added to mortgage maturity date following modification. *Max Delinquency* is the maximum number of months in arrears cumulated by the borrower before being modified. *IR Spread* is the difference between mortgage interest rate at origination and Freddie Mac 30-Year interest rate curve. Ump_{12}^{lag2Yr} is the 1-year growth rate of State-level Unemployment, lagged by 2 years. The $PostHAMP$ period spans over the years following lift of HAMP program (from 2017 onwards) and is activated using a dummy variable for mortgages modified in this period. The sample includes mortgages originated from 1999 to 2022 and observed from 1999 to 2023. ***, **, * denote statistical significance at the 1%, 5% and 10% levels respectively.

Variable	Prepaid/Matured	60+Delinquent	Liquidation
Credit Score	1.002195***	0.9962271***	0.9980334***
	(0.0000515)	(0.0000572)	(0.0000792)
Debt-to-Income	1.002369***	1.001248***	1.004136***
	(0.000225)	(0.000255)	(0.000338)
Loan-to-Value	0.9912989***	1.004045***	1.017341***
	(0.0002068)	(0.0002438)	(0.0003328)
Joint	1.171496***	0.86469***	0.7955215***
	(0.0063047)	(0.0053854)	(0.0069189)
Judicial	0.8503284***	1.187731***	0.9673221***
	(0.0051944)	(0.0081355)	(0.0092186)
Non Recourse	1.115828***	0.8693013***	1.07904***
	(0.007164)	(0.0069035)	(0.0117023)
Not Single-Family	1.078932***	0.9438956***	1.074314***
	(0.0074207)	(0.0078188)	(0.0118085)
TPO	0.9638948***	1.112239***	1.23321***
	(0.0052517)	(0.007067)	(0.0110813)
Purchase	1.136208***	1.13697***	1.169937***
	(0.0073679)	(0.0084236)	(0.0116084)
HAMP Flag	0.9181498***	0.8864985***	0.5721754***
	(0.005527)	(0.0062571)	(0.0054191)
IR Change (Neg)	1.017181***	1.016871***	1.011519***
	(0.0001155)	(0.0001366)	(0.0001894)
Term Extension	0.9725295***	0.9761562***	0.9645374***
	(0.0003507)	(0.0003703)	(0.0005333)
Max Delinquency	0.983348***	1.019223***	1.019482***
	(0.0004685)	(0.0003538)	(0.0004444)
Post-HAMP*Credit Score	0.9997523**	1.001226***	1.001424***
	(0.0001248)	(0.0001201)	(0.000327)
Post-HAMP*Debt-to-Income	0.9950373***	0.9995098	0.993776***
	(0.0005262)	(0.000543)	(0.0014596)
Post-HAMP*Loan-to-Value	1.006153***	0.9990827**	0.9941732***
	(0.0004517)	(0.0004509)	(0.0011287)
Post-HAMP*Joint	0.9225668***	0.9213674***	0.9545786
	(0.0125819)	(0.0125698)	(0.0359702)
Post-HAMP*Judicial	1.019254	0.7889307***	0.8945352***
	(0.0149914)	(0.0114014)	(0.0356597)
Post-HAMP*Non Recourse	1.049443***	1.094563***	0.9726522
	(0.0186161)	(0.019621)	(0.047851)

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Table 4.9

Variable	Prepaid/Matured	60+Delinquent	Liquidation
Post-HAMP*Not Single-Family	1.156986***	0.9186019***	0.7683404***
	(0.0176207)	(0.0147912)	(0.0327936)
Post-HAMP*TPO	0.6665758***	0.9571944**	0.6761786***
	(0.0152783)	(0.0175635)	(0.0344376)
Post-HAMP*Purchase	1.001321	1.034447**	1.020957
	(0.015414)	(0.0157892)	(0.0415037)
Post-HAMP*HAMP Flag	0.4821837***	1.499688***	1.815466***
	(0.0142278)	(0.0299649)	(0.1010269)
Post-HAMP*IR Change (Neg)	1.000452	1.000226	0.9854018***
	(0.0006502)	(0.000506)	(0.0011956)
Post-HAMP*Term Extension	1.012693***	1.015209***	1.023894***
	(0.0008365)	(0.0007931)	(0.0020978)
Post-HAMP*Max Delinquency	1.012687***	0.9981481**	1.000064
	(0.0010985)	(0.0007596)	(0.0020614)
IR Spread	1.143352***	1.18519***	1.256571***
	(0.0033533)	(0.0030154)	(0.0055495)
Ump_{12}^{lag2Yr}	0.9172838***	1.057138***	1.137438***
	(0.0020334)	(0.0009783)	(0.0021098)
Log-likelihood	-13957737		
Wald Chi-Sq	101335.82		
Pseudo-R^2	0.0457		
N. Observations	28,869,343		
N. Mortgages	481,703		

Table 4.10: Determinants of Mortgage Post-Modification Outcomes by HAMP and CARES Act Period: Marginal Effects

The Table shows average marginal effects of explanatory variables on the different outcomes of multinomial logit regression. The baseline outcome is *Current*, and it is not displayed being the reference category. The outcomes reported are: $60+$ *Delinquent*, *Prepaid/Matured* and *Liquidation*. Standard errors of marginal effects are calculated using the delta method and are reported in parentheses. *Credit Score* is borrower's Credit Score at origination. *Debt-to-Income* is the sum of borrower's monthly debt payments, including housing expenses that incorporate mortgage payment, divided by total monthly income used for underwriting. *Joint* captures loans with more than one borrower. *Loan-to-Value* is the ratio between $Balance_t$ and $PropertyPrice_t$at origination. *Judicial* differentiate Judicial from Non-judicial states; *Non Recourse* differentiate Recourse States from Non-recourse states; *Not Single-family* distinguished Single-Family from other property types. TPO catches mortgages originated by Third Parties; *Purchase* separates Purchase from Refinance loan purpose; *HAMP Flag* absorbs the effect of mortgages eligible under HAMP program. *IR Change (Neg)* is the percentage change of mortgage interest rate before and after modification; it is populated only when it takes negative values. *Term Extension* is the number of additional years added to mortgage maturity date following modification. *Max Delinquency* is the maximum number of months in arrears cumulated by the borrower before being modified. *IR Spread* is the difference between mortgage interest rate at origination and Freddie Mac 30-Year interest rate curve. Ump_{12}^{lag2Yr} is the 1-year growth rate of State-level Unemployment, lagged by 2 years. The $PostHAMP$ period spans over the years following lift of HAMP program (from 2017 onwards) and is activated using a dummy variable for mortgages modified in this period. The $CARES$ period spans over the years of CARES Act implementation (from March 2020 to September 2021) and is activated using a dummy variable for mortgages modified in this period. The sample includes mortgages originated from 1999 to 2022 and observed from 1999 to 2023. ***, **, * denote statistical significance at the 1%, 5% and 10% levels respectively.

Variable	Prepaid/Matured	60+Delinquent	Liquidation
Credit Score	0.0000137***	-0.000515***	-0.00000328***
	(0.000000248)	(0.00000775)	(0.000000202)
Debt-to-Income	0.00000995***	0.0001673***	0.0000107***
	(0.00000107)	(0.0000346)	(0.000000858)
Loan-to-Value	-0.0000453***	0.0005472***	0.0000453***
	(0.000001)	(0.0000329)	(0.00000086)
Joint	0.0008862***	-0.0197216***	-0.000545***
	(0.0000261)	(0.0008394)	(0.0000219)
Judicial	-0.0009108***	0.0236531***	-0.0001891***
	(0.0000286)	(0.0009368)	(0.0000243)
Non Recourse	0.0006582***	-0.018777***	0.000296***
	(0.0000329)	(0.0010312)	(0.0000296)
Not Single-Family	0.0004214***	-0.0078847***	0.0002358***
	(0.0000349)	(0.001099)	(0.0000295)
TPO	-0.0002657***	0.014371***	0.0005196***
	(0.0000262)	(0.0008628)	(0.0000231)
Purchase	0.0005101***	0.0175206***	0.0003644***
	(0.0000327)	(0.0010394)	(0.0000264)
HAMP Flag	-0.0002904***	-0.016126***	-0.0015028***
	(0.000029)	(0.0009699)	(0.0000262)
IR Change (Neg)	0.0000666***	0.0022574***	0.0000218***
	(0.000000588)	(0.0000183)	(0.000000481)
Term Extension	-0.0001119***	-0.0032365***	-0.0000854***
	(0.00000173)	(0.0000513)	(0.00000144)
Max Delinquency	-0.0000968***	0.0025978***	0.0000426***
	(0.00000227)	(0.0000472)	(0.00000108)
PostHAMP*Credit Score	0.00000897***	-0.0003455***	-0.0000000857
	(0.000000516)	(0.0000172)	(0.000000382)
PostHAMP*Debt-to-Income	-0.000011***	0.0002213***	-0.00000337*
	(0.00000214)	(0.0000769)	(0.00000175)
PostHAMP*Loan-to-Value	-0.0000155***	0.0004637***	0.0000145***
	(0.00000179)	(0.0000607)	(0.00000142)
PostHAMP*Joint	0.0004238***	-0.0322152***	-0.0002777***
	(0.0000567)	(0.0019374)	(0.000044)
PostHAMP*Judicial	-0.0003779***	-0.0124479***	-0.0001758***
	(0.0000598)	(0.0020511)	(0.000047)

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Table 4.10

Variable	Prepaid/Matured	60+Delinquent	Liquidation
PostHAMP*Non Recourse	0.0006107***	-0.0062758**	0.0000275
	(0.0000824)	(0.0025747)	(0.00006)
PostHAMP*Not Single-Family	0.0011695***	-0.0207193***	-0.0002076***
	(0.0000719)	(0.0021392)	(0.0000463)
PostHAMP*TPO	-0.0016168***	0.0095001***	-0.0001935***
	(0.0000855)	(0.0027054)	(0.0000572)
PostHAMP*Purchase	0.0003771***	0.021968***	0.0001212**
	(0.0000647)	(0.0022241)	(0.0000495)
PostHAMP*HAMP Flag	-0.0032066***	0.0426343***	0.0000163
	(0.0000993)	(0.0030152)	(0.0000636)
PostHAMP*IR Change (Neg)	0.0000559***	0.002714***	-0.00000665***
	(0.00000247)	(0.0000641)	(0.00000164)
PostHAMP*Term Extension	-0.0001119***	-0.0010171***	-0.00000948***
	(0.00000173)	(0.0001085)	(0.00000243)
PostHAMP*Max Delinquency	-0.0000281***	0.0025008***	0.0000188***
	(0.00000434)	(0.0001024)	(0.0000021)
CARES*Credit Score	0.0000154***	-0.0005366***	0.000000166
	(0.00000159)	(0.0000382)	(0.000000347)
CARES*Debt-to-Income	-0.0000134**	-0.0007177***	0.00000103
	(0.00000666)	(0.0001747)	(0.00000142)
CARES*Loan-to-Value	0.00000172	0.000266*	-0.00000274**
	(0.0000053)	(0.0001436)	(0.00000122)
CARES*Joint	0.0011351***	-0.0391482***	-0.0000614
	(0.0001675)	(0.0042376)	(0.0000421)
CARES*Judicial	-0.0009266***	0.0033712	-0.00000627
	(0.0001732)	(0.0043301)	(0.0000434)
CARES*Non Recourse	0.0010156***	-0.0097385*	0.000113*
	(0.0002112)	(0.0051877)	(0.0000602)
CARES*Not Single-Family	0.0011759***	-0.0181595***	-0.00000391
	(0.0001958)	(0.004428)	(0.0000417)
CARES*TPO	-0.0023728***	-0.0095485	-0.0004707***
	(0.0003178)	(0.0073632)	(0.0000797)
CARES*Purchase	0.0001859	0.0387844***	0.0002592***
	(0.0001817)	(0.0048639)	(0.0000658)
CARES*HAMP Flag	-0.0051726***	0.0150052*	-0.0005115***
	(0.0003963)	(0.0088407)	(0.0000962)
CARES*IR Change (Neg)	0.000109***	0.0013116***	-0.0000046***
	(0.00000691)	(0.0001275)	(0.00000177)
CARES*Term Extension	-0.000055***	-0.0027611***	-0.0000106***
	(0.0000034)	(0.0002668)	(0.00000332)
CARES*Max Delinquency	-0.0000685***	0.0027675***	0.00000481***
	(0.0000156)	(0.0002428)	(0.00000184)
IR Spread	0.0004946***	0.0230598***	0.0004755***
	(0.0000146)	(0.0003481)	(0.0000105)
Ump_{12}^{lag2Yr}	-0.0005003***	0.0077857***	0.0002914***
	(0.0000111)	(0.0001259)	(0.00000456)
Log-likelihood	-13953540		
Wald Chi-Sq	102845.23		
Pseudo-R^2	0.0460		
N. Observations	28,869,343		
N. Mortgages	481,703		

Table 4.11: Determinants of Mortgage Post-Modification Outcomes by HAMP and CARES Act Period: Relative Risk Ratios

The Table shows relative risk ratios of explanatory variables on the different outcomes of multinomial logit regression. The baseline outcome is $Current$, and it is not displayed being the reference category. The outcomes reported are: $60 + Delinquent$, *Prepaid/Matured* and $Liquidation$. Standard errors of marginal effects are calculated using the delta method and are reported in parentheses. *Credit Score* is borrower's Credit Score at origination. *Debt-to-Income* is the sum of borrower's monthly debt payments, including housing expenses that incorporate mortgage payment, divided by total monthly income used for underwriting. *Joint* captures loans with more than one borrower. *Loan-to-Value* is the ratio between $Balance_t$ and $PropertyPrice_t$at origination. *Judicial* differentiate Judicial from Non-judicial states; *Non Recourse* differentiate Recourse States from Non-recourse states; *Not Single-family* distinguished Single-Family from other property types. TPO catches mortgages originated by Third Parties; *Purchase* separates Purchase from Refinance loan purpose; *HAMP Flag* absorbs the effect of mortgages eligible under HAMP program. *IR Change (Neg)* is the percentage change of mortgage interest rate before and after modification; it is populated only when it takes negative values. *Term Extension* is the number of additional years added to mortgage maturity date following modification. *Max Delinquency* is the maximum number of months in arrears cumulated by the borrower before being modified. *IR Spread* is the difference between mortgage interest rate at origination and Freddie Mac 30-Year interest rate curve. Ump_{12}^{lag2Yr} is the 1-year growth rate of State-level Unemployment, lagged by 2 years. The $PostHAMP$ period spans over the years following lift of HAMP program (from 2017 onwards) and is activated using a dummy variable for mortgages modified in this period. The $CARES$ period spans over the years of CARES Act implementation (from March 2020 to September 2021) and is activated using a dummy variable for mortgages modified in this period. The sample includes mortgages originated from 1999 to 2022 and observed from 1999 to 2023. ***, **, * denote statistical significance at the 1%, 5% and 10% levels respectively.

Variable	Prepaid/Matured	60+Delinquent	Liquidation
Credit Score	1.002185***	0.9962301***	0.9980356***
	(0.0000515)	(0.0000572)	(0.0000792)
Debt-to-Income	1.002329	1.001262	1.004147
	(0.000225)	(0.0002551)	(0.000338)
Loan-to-Value	0.991308	1.004045	1.017344
	(0.0002067)	(0.0002438)	(0.0003328)
Joint	1.171229	0.8647423	0.795551
	(0.006302)	(0.0053861)	(0.0069194)
Judicial	0.8503827	1.187707	0.9673203
	(0.0051938)	(0.0081359)	(0.009219)
Non Recourse	1.115492	0.8693559	1.079075
	(0.0071606)	(0.0069043)	(0.011703)
Not Single-Family	1.078964	0.9438889	1.074308
	(0.0074196)	(0.007819)	(0.0118086)
TPO	0.9646501	1.111899	1.232898
	(0.0052558)	(0.0070649)	(0.0110784)
Purchase	1.137053	1.136675	1.169666
	(0.0073715)	(0.0084222)	(0.0116064)
HAMP Flag	0.9193355	0.8861933	0.5720228
	(0.0055352)	(0.0062555)	(0.0054177)
IR Change (Neg)	1.017162	1.016877	1.011527
	(0.0001156)	(0.0001366)	(0.0001894)
Term Extension	0.9724664	0.9761867	0.9645571
	(0.0003506)	(0.0003704)	(0.0005333)
Max Delinquency	0.9833292	1.019239	1.019497
	(0.0004685)	(0.0003539)	(0.0004446)
PostHAMP*Credit Score	0.9995878	1.001451	0.0004446
	(0.0001352)	(0.0001272)	(0.0003463)
PostHAMP*Debt-to-Income	0.995255	1.000218	0.993248
	(0.00057)	(0.0005721)	(0.0015479)
PostHAMP*Loan-to-Value	1.005519	0.9991005	0.995992
	(0.0004898)	(0.000472)	(0.0011911)
PostHAMP*Joint	0.9083313	0.9289957	0.9441494
	(0.0135328)	(0.0134342)	(0.0377466)
PostHAMP*Judicial	1.052611	0.7732463	0.8720465
	(0.0169095)	(0.0118774)	(0.0368709)

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Table 4.11

Variable	Prepaid/Matured	60+Delinquent	Liquidation
PostHAMP*Non Recourse	1.028846	1.103074	0.9417425
	(0.020528)	(0.021158)	(0.0499246)
PostHAMP*Not Single-Family	1.178874	0.9185805	0.7496319
	(0.0195383)	(0.0157177)	(0.0344222)
PostHAMP*TPO	0.6910065	0.9567185	0.6933866
	(0.0167946)	(0.018245)	(0.036023)
PostHAMP*Purchase	0.9925348	1.018729	0.9761059
	(0.0167005)	(0.016519)	(0.0419905)
PostHAMP*HAMP Flag	0.5021974	1.503699	1.868325
	(0.0154673)	(0.0311103)	(0.1058698)
PostHAMP*IR Change (Neg)	1.000416	1.001699	0.9865365
	(0.0007429)	(0.0005661)	(0.0012841)
PostHAMP*Term Extension	0.9724664	1.01728	1.026815
	(0.0003506)	(0.0008372)	(0.002199)
PostHAMP*Max Delinquency	1.013249	0.9978602	1.000279
	(0.0011816)	(0.0008012)	(0.0020978)
CARES*Credit Score	0.9998673	0.999732	1.001735
	(0.0002736)	(0.0002802)	(0.0009236)
CARES*Debt-to-Income	0.9944288	0.993309	0.9976184
	(0.001196)	(0.0013297)	(0.0038177)
CARES*Loan-to-Value	1.009407	0.9979791	0.9762088
	(0.0009779)	(0.001117)	(0.0028749)
CARES*Joint	0.991615	0.8587025	1.016726
	(0.0287894)	(0.0279243)	(0.109935)
CARES*Judicial	1.001328	0.862708	1.019822
	(0.0314131)	(0.028863)	(0.1173053)
CARES*Non Recourse	1.051651	1.069026	1.209737
	(0.0361962)	(0.0438456)	(0.1556425)
CARES*Not Single-Family	1.102047	0.9210379	0.9015201
	(0.0346245)	(0.0332508)	(0.1003655)
CARES*TPO	0.6589226	0.8335474	0.1768169
	(0.0442978)	(0.0471866)	(0.0622191)
CARES*Purchase	0.9546135	1.168083	1.653011
	(0.0311047)	(0.0413023)	(0.2095959)
CARES*HAMP Flag	0.4128947	1.255749	0.4760654
	(0.0431091)	(0.0831138)	(0.2025611)
CARES*IR Change (Neg)	1.003872	0.9933532	0.9784987
	(0.0013642)	(0.0010861)	(0.0033333)
CARES*Term Extension	1.013002	1.00303	1.004431
	(0.0009061)	(0.0019692)	(0.0066398)
CARES*Max Delinquency	1.008235	1.00183	0.9968583
	(0.0027563)	(0.0019389)	(0.0046863)
IR Spread	1.139167	1.1865	1.257694
	(0.0033456)	(0.0030303)	(0.0055612)
Ump_{12}^{lag2Yr}	0.9142224	1.058715	1.138602
	(0.002033)	(0.0009814)	(0.0021113)
Log-likelihood	-13953540		
Wald Chi-Sq	102845.23		
Pseudo-R^2	0.0460		
N. Observations	28,869,343		
N. Mortgages	481,703		

Chapter 5

Residential Mortgages Post-Default Resolutions across Mortgage Market Breaks

5.1 Introduction

Residential mortgages represent an important market in major economies. Focusing on the US commercial banking sector, in 2023 residential mortgages made up 23.01% of total assets, evenly divided between mortgage-backed securities (12.6%) and residential real estate loans (10.4%), amounting to 5.27 trillion dollars (Board of Governors of the Federal Reserve System - Data (2023)). It should be noted that the majority of originated loans are subsequently securitised and sold to Government Sponsored Enterprises (GSEs) (66% of the total, according to Fuster et al. (2022) and Banking Strategist (2022)). In total, the US single family residential mortgage market volume approached \$13 trillion in Q3 2022 (Banking Strategist (2022)), and continues to grow over time. Hence, the considerable attention directed towards this market and the substantial effort that lending institutions invest to adequately manage the risks associated with mortgage financing is not surprising.

It is widely acknowledged that mortgage defaults and subsequent foreclosures exert detrimental impacts on the local economy (Campbell et al. (2011*b*), Towe and Lawley (2013), Chomsisengphet et al. (2018)) and disrupt social equilibrium (Ellen et al. (2013), Hall et al. (2015)). The key question pertains to the existence of an escape route from default and, from a risk management viewpoint, the optimal method of identifying it. Comprehending the determinants of post-default is crucial, as each outcome yields varying levels of profitability for lenders/investors. For instance, if a borrower can self-cure, as opposed to being foreclosed or modified, this is advantageous for both the lender and the obligor. Concurrently, from a risk-management perspective, it can facilitate a refined strategy to promptly address the issue and obtain a positive resolution. Lastly, it sheds light on lending institutions' preferences in guiding the borrower outside their delinquency status.

The final empirical chapter of the Thesis scrutinises this particular facet of mortgage lending (i.e. post-default outcomes), addressing questions not yet covered by the existing body of literature. The primary concern is the representativeness of the data. Prior research in this area has predominantly focused on specialized niche portfolios, classified either as sub-prime or limited by geographical constraints. Remarkably, the post-default outcomes of conventional mortgages, which constitute the bulk of residential mortgage lending in the US, have not been comprehensively analysed on a national level. This omission prompts several questions: Do the factors that influence the post-default outcomes of sub-prime mortgages affect conforming, prime loans in the same or different ways? Are their effects intensified or attenuated? To tackle these queries, the study first conducts an extensive analysis that encompasses a wider range of the US mortgage market, focusing on conforming loans securitized by Freddie Mac. Crucially, the chapter investigates how evolving policies and market disruptions have influenced the behaviour of consumers and lenders. The Global Financial Crisis and the subsequent introduction of borrower support programs have marked a pivotal period in the US mortgage market. Thus, the research seeks to determine whether these events have had a differential impact on the principal determinants of post-default resolutions, and whether this impact has been temporary or enduring. By analysing over 20 years of performance data, this study aims to shed light on these questions.

The interest in post-default outcomes is obviously not novel. The pioneering papers that analysed post-default resolutions were those by Ambrose and Capone (1996), Ambrose and Capone (1998), Capozza and Thomson (2006) and Phillips and VanderHoff (2004). Ambrose and Capone (1998) and Ambrose and Capone (1996) first distinguished default from foreclosure, clarifying a common misconception that the two outcomes overlap. Capozza and Thomson (2006) delved into the post-default transition to either a cure or Real Estate Owned (REO) status[1], revealing the mortgage characteristics that influence persistence in each state. A more recent study by Liu and Sing (2018) focused specifically on mortgage cures, while Phillips and VanderHoff (2004) augmented the post-default analysis by introducing prepayment as an additional outcome. However, with the sole exception of Phillips and VanderHoff (2004), these early studies examined only a single post-default outcome at a time. Furthermore, despite these papers providing an initial exploration of post-default resolutions, they were composed (or utilised data) prior to one of the most significant disruptions in the mortgage market, which also altered post-default dynamics.

The Global Financial Crisis (GFC), rooted in subprime mortgages, paved the way for significant changes in financial markets and the associated literature. The dramatic escalation in defaults, followed by the introduction of policies to safeguard borrowers, induced a shift in both lender and consumer behaviour, which in turn influenced post-default resolutions. Among the most impactful measures, the Home Affordable Modification Program (HAMP) and the Home Affordable Repurchase Program (HARP)[2] were designed to encourage mortgage modifications and mortgage refinancing, respectively. HAMP assisted borrowers facing financial hardship in fulfilling scheduled repayments by encouraging lenders/servicers to alter contractual terms, thereby offering a more manageable deal. Conversely, HARP supported borrowers in negative equity by refinancing their mortgages and reducing the principal amount to partially transfer house depreciation to the lender.

From this point onwards, a considerable volume of literature began focusing on modifications. Academic research evolved from a handful of studies examining modification

[1] Real Estate Owned (REO) acquisition refers to foreclosed properties that are owned by the lender and are not sold at an auction. It indicates that the borrower is no longer the owner of the property and cannot dwell in the house.

[2] Both these programs were promulgated under the Troubled Assets Relief Program (TARP).

as a post-default outcome, to a comprehensive body of work aiming to comprehend renegotiation procedures and their implications, as explored by Agarwal et al. (2017), Boehm and Schlottmann (2020) and Haughwout et al. (2009). Additionally, the role of servicers, as discussed by Reid et al. (2014) and Agarwal et al. (2017), and the influence of securitisation, as studied by Piskorski et al. (2010), Kruger (2018), Ghent (2011) and Adelino et al. (2013), on modification volumes are also prominent areas of study.

The increase in mortgage renegotiations bears significance for our research as it introduces a novel and crucial outcome to post-default resolutions, a factor previously unexplored in earlier studies. Reference studies that regard renegotiation as one of the post-default outcomes include those by Been et al. (2013), Chan et al. (2014) and Voicu et al. (2012). Both Been et al. (2013) and Chan et al. (2014) utilise mortgages originated in New York City to demonstrate the loan-, borrower-, and neighbourhood characteristics that are most influential in determining cure, repossession, or modification for delinquent mortgages. Conversely, Voicu et al. (2012) incorporate product features and borrower demographics to investigate the dynamics associated with post-default and foreclosure proceedings. Nonetheless, beyond these authors, literature on post-default outcomes (including modification) has not expanded at the same rate as in the aforementioned areas related to mortgage renegotiations.

Moreover, even these latter studies fail to fully investigate post-delinquency dynamics. Firstly, the sample period employed barely overlaps with the enactment of federal policies, and crucially, these are not integrated into the modelling process. The follow-up of post-default performance extends until 2010 at most, as seen in Been et al. (2013), and concludes even earlier in the works of Chan et al. (2014) and Voicu et al. (2012). Thus, given that HAMP was initially implemented in 2009, the development samples utilised either encompass the introduction of government schemes for a minimal duration, or they entirely omit it. Secondly, the geographical data coverage in Been et al. (2013) and Chan et al. (2014) is confined to New York City, whereas Voicu et al. (2012) sample solely incorporates subprime loans. Consequently, the authors' conclusions might not be readily generalisable to other mortgage sectors and could lack comprehensive representation of the entire US mortgage market.

Our research contributes to existing literature in several distinct ways. Firstly, we explicitly delineate the impact of an unfolding crisis and subsequent policy interventions on post-default outcomes, examining how these factors alter its dynamics. The crisis, coupled with the implementation of the HAMP program, introduced new standards for dealing with delinquent borrowers, primarily to encourage mortgage modifications over foreclosures. Consequently, we specifically scrutinise the effect of the HAMP period on post-default resolutions, rather than relegating it to the background or intentionally sidestepping it. Significantly, by utilising a data sample spanning from 1999 to 2022, we can directly observe the events preceding, during, and following the implementation of the government scheme. What changes can we discern in the propensity for curing, foreclosing, or modification? It is vital to comprehend the behavioural shifts observable in more recent, previously unexamined periods and to distinctly differentiate government support in post-delinquency resolutions across different phases, given that some policies have been fully standardised and incorporated into the financial system. We discover that the pre-, during- and post-crisis periods, along with the embedded policy alterations, significantly influenced borrowers' exit from default status. We also distinguish characteristics that remain stable across policy cycles from those that undergo a shift due to the period under examination. Some variables permanently change following the introduction of government programmes, while others display a temporary permutation.

A corollary of the above pertains to the origination period employed in prior research. The majority of frequently cited studies incorporate mortgages originated up to 2008 (Been et al. (2013), Chan et al. (2014)) or 2006 (Voicu et al. (2012)). Nevertheless, it is widely acknowledged that subsequent to the Global Financial Crisis (GFC), both mortgage scrutiny and origination underwent significant alterations due to the implementation of stricter lending practices and more rigorous underwriting standards (Courchane et al. (2015)). The exclusive consideration of mortgages originated before the crisis might produce results that are no longer pertinent today. Our research supplements existing studies by investigating post-default outcomes for mortgages originated in the post-crisis period, specifically after 2009.

Lastly, much of the existing literature in this research field tends to concentrate on a restricted geographical area or examines a specific segment, such as subprime lending. However, it is acknowledged that subprime borrowers possess a markedly different risk profile, and their behaviour post-default can vary significantly (Capozza and Thomson (2006)). Furthermore, whilst subprime lending was determinant for US financial stability, it constitutes only a small fraction of the entire US mortgage market (Adelino et al. (2016) and Federal Reserve Bank of New York (2024)). Utilising conforming loans securitised by Freddie Mac, our study offers a fresh perspective in the post-default literature. This is vital, as it's important to note that banks do not exclusively hold subprime/jumbo loans, and Freddie Mac data could accurately represent the ”prime” segment of the mortgage balance-sheet. Thus, we enhance the current literature by determining if there is consistency or discrepancy with prior findings related to subprime mortgages. Moreover, by leveraging a broad national sample, we underline the significance of new post-default determinants, previously unexplored in this context, and their impact on post-default resolutions.

5.2 Data

This study utilises loan-level and borrower-level data from nearly 2 million defaulted mortgages. The dataset comes from the same pool of Freddie Mac data employed for the first and second empirical studies. In this case, we employ loans originated between the first quarter of 1999 and the first quarter of 2022, whose status is monitored until the second quarter of 2022. States such as California and Florida, in line with the demographic distribution in the United States, are more prominently represented in the sample (Figure 5.1).

As described in Section 4.2, loans performance is monitored with monthly frequency since the date of origination. Amongst performance variables, repayment information is crucial in determining the default status of the mortgage and hence identify the loans that are included in our development sample. Two indicators are available to monitor the repayment performance of each loan. The first indicator is the *Zero Balance Code*, which shows the reason why the loan balance has been reduced to zero, including charge-off, real estate owned (REO) acquisition, repurchase prior to property disposition and third-party sale. The second indicator is *Delinquency Status*, which refers to the number of days a borrower has been delinquent. Both variables are used to identify high-risk customers and trigger the default status, as the first occurrence of either 90-days delinquency or *Zero Balance Code* being populated. This aligns with the recently updated regulatory definition of default (Bank for International Settlements (BIS) (2013)). Based on this definition, 1,956,859 mortgages in the initial sample experienced default during the observation period. We consider the occurrence of first default as the starting point of our analysis, and thus, we exclude any observations before the initial default occurs.

Figure 5.2a and Figure 5.2b display two complementary aspects of the evolution of mortgage defaults during our sample period. Figure 5.2a shows that a large share in defaults occurred in the years 2009-2010, subsequent to the commencement of the Global Financial Crisis (GFC). Additionally, there is a notable isolated surge in delinquencies recorded in 2020, coinciding with the Covid-19 pandemic. Figure 5.2b portrays the default rate by year of origination, underscoring that mortgages initiated just prior to the crisis have a higher propensity to default, even though mortgages established post-GFC continue to contribute to the delinquency population.

Alongside *Delinquency Status* and *Zero Balance Code*, *Modification Flag* is another key variable that assists in determining the ultimate post-default outcomes. Altogether, these are identified as $Cure$, *Liquidation*, *Delinquency*, $Successful$ and *Unsuccessful (Failed) Modification*. $Cure$, *Liquidation* and $Modification$ are considered as terminal status. Once the borrower enters any of these three statuses, we drop all observations following the event date. However, given that a mortgagor can transition between different statuses throughout the entire observation period, a hierarchy is instituted to ensure no severe event is overlooked. We shall now elaborate on the reasoning behind the assignment to each of these statuses.

The final status of $Cure$ is assigned when a borrower accumulates six months in the current status, that is, when *Delinquency Status* equals zero. Typically, lending institutions regard a loan as cured once it has completed the probation period, a minimum time interval during which the borrower demonstrates a return to the scheduled repayment behaviour. Given the multiple lenders in the dataset, it is unfeasible to determine the discretionary probation period established by each institution. Consequently, the six-month rule is applied uniformly and is deemed appropriate for this asset class. Nevertheless, to ensure that the complete cessation of delinquent behaviour is effectively sustained, we also verify whether the mortgage is eventually foreclosed at the end of the observation window. In such a case, we supersede the $Cure$ status with $Liquidation$, as the latter is considered the most severe event.

The *Modification Flag* is activated each time there is a change in the contractual terms of the mortgage, facilitating the identification of post-default $Modification$ outcomes. Upon the modification of a mortgage, we can ascertain the impact on the interest rate, loan term or outstanding balance by comparing the value at the time of modification with that of the preceding month(s). Additionally, we can determine if the loan has been modified more than once. However, to prevent an insufficient number of observations in each modification's final status, we avoid constructing an excessively detailed target status for each type or number of modifications. Conversely, we differentiate between $Successful$ and $Unsuccessful$ modifications by monitoring if the loan eventually gets liquidated. Our analysis aims to comprehend which mortgage features influence a positive or negative renegotiation.

The *Zero Balance Code* is useful in identifying the post-default outcome of $Liquidation$, triggered when any of the following values are assigned: REO (Real Estate Owned)

Disposition[3], Short Sale[4], Charge Off[5], or Third Party Sale[6], which all signify property liquidation. *Liquidation* is the most severe final status for both borrower and lender, as it involves the seizure of the borrower's property and a potential loss for the credit institution.

The post-modification outcomes' evolution is depicted in Figure 5.3a. The years succeeding the GFC are dominated by *Liquidation*, although a significant proportion of *Cure* and *Successful Modifications* is also observed. From 2010 onwards, a consistent decrease in the proportion of modified mortgages is noted. Interestingly, a slight decline in $Failed$ modifications over time is observed, making way for more $Successful$ modifications. This could potentially indicate a more effective and targeted approach by lenders/servicers in granting renegotiations. Alternatively, it could be a consequence of an enhanced economic environment. This is corroborated by Figure 5.3b, which reveals that successful modifications are proportionately distributed across various origination periods, albeit more significant for mortgages originated prior to the crisis.

In addition to performance metrics, data on origination and performance can assist in profiling each defaulted mortgage in the sample. Origination data encompasses borrower-, property-, and mortgage-related characteristics measured at the issuance time. The characteristics of defaulted mortgages are delineated by default year in Table 5.1 and Table 5.2, and by final outcome in Table 5.3 and Table 5.4.

[3] Real Estate Owned (REO) acquisition refers to foreclosed properties that are owned by the lender and were not sold at an auction.

[4] A short sale in real estate is when a property is offered at a price lower than the amount due on the current owner's mortgage. It typically indicates a financially distressed homeowner who needs to sell the property before the lender seizes it in foreclosure.

[5] A charge-off is an accounting action taken by a lender when they determine that a borrower's home loan is unlikely to be collected. This usually occurs after the borrower has been significantly delinquent on payments. It often precedes foreclosure.

[6] A third party sale refers to a transaction where a property is sold to a third party, typically not the original lender or the homeowner. This generally occurs when the borrower cannot keep up with repayments and the mortgage is consequently foreclosed.

Table 5.1 reveals a dynamic trend in the characteristics of delinquent borrowers, reflecting the evolution of the underlying population, while certain features remain constant. For instance, borrowers purchasing their homes as primary dwellings account for 90% of the defaulted population across all default periods. In contrast, loans originated by unspecified third parties (*Third-Party-Originations*) have seen a substantial decrease in their share over time. This category is solely attributed to mortgages originated before 2008, since Freddie Mac started collecting more detailed information from that year onwards to disclose whether a Broker or Correspondent played a role in the origination of each loan. *Single-family* properties represent the most common property type, although there has been a noticeable increase in *Planned Unit Development* and *Condominium* in recent years. The proportion of *Joint* and *Single* borrowers in defaulted loans remained stable until 2012. From that year, mortgages backed by a single applicant began to exhibit a higher propensity to default.

Similar patterns are observed for continuous variables by the year of default, as displayed in Table 5.2. These shifts in population also mirror changes in Freddie Mac guidelines or market trends. This is particularly evident when examining *Balance* and *Interest Rate* at origination. The former distinctly demonstrates the rising upper limit in conforming size imposed by GSEs, a consequence of escalating property prices and inflationary trends. The latter, however, corresponds with the decreasing policy and mortgage interest rates. Interestingly, the *Credit Score* of the defaulted population is only slightly affected by the stricter eligibility criteria implemented by Freddie Mac, as the average credit score has seen only a marginal increase over time. Moreover, it is observed that defaulted borrowers in our sample are, on average, prime, which sets our sample apart from previously analysed populations. Similar to *Credit Score*, *Debt-to-Income* of the defaulted population remains largely unaffected by changes in eligibility criteria, with the average hovering around 35% throughout the entire period.

Table 5.3 reveals that borrowers who enter default status exhibit heterogeneity in terms of Purpose. No discernible pattern emerges across varying post-default outcomes when considering the distributions of *Purchase*, *Cash-Out Refinance*, and *Non*

Cash-Out Refinance. However, the *Channel* variable indicates an uptick in *Third-Party-Originations* (TPOs) for liquidated and modified mortgages. As inferred during the discussion of Table 5.1, *Third-Party-Originations* may also reflect the origination period and the impact of the Global Financial Crisis (GFC) on riskier mortgages. In terms of occupancy, *Investment* and *Second Home* demonstrate a higher likelihood of liquidation and lower probability of modification. This aligns with the initial eligibility criteria of HAMP (U.S. Department of the Treasury (2023*a*)), which limited modifications to borrowers purchasing their primary residence. Consequently, alternative occupancy types have been disadvantaged, being more prone to liquidation due to the absence of external support.

The distribution of variables such as *Credit Score*, *Loan-to-Value (LTV)*, *Debt-to-Income*, *Interest Rate*, *Balance*, alongside time-variant variables measured at the last observation date, including *Loan Age*, *Remaining Months to Maturity* and *Time Since Default*, are presented in Table 5.4. The *Credit Score*, represented by the FICO score, demonstrates that lower scores are common among borrowers who receive a modification or are liquidated. The *Debt-to-Income* ratio, which is the sum of the borrower's monthly debt payments (including housing expenses related to the underwritten mortgage) divided by the total monthly income used to underwrite the loan, is typically higher for modified and liquidated loans, both on average and across quantiles. A similar trend is observed for *Loan-to-Value*, the ratio of the mortgage loan amount to the appraised value of the property at origination. The same rationale for using *Loan-to-Value* at origination over *Updated Loan-to-Value* explained in Section 4.2 is applied in this case too. The *Interest Rate* at origination indicates that lower mortgage rates are typically associated with borrower curing or continued delinquency. Meanwhile, the *Balance* at origination does not specifically indicate a post-default outcome, although we will observe that it plays an important role in influencing post-default resolutions. Lastly, *Loan Age* and *Time Since Default* provide an interesting insight into the defaulted mortgages analysed. As they are both measured at the last observation point of each loan, they reveal a correlated aspect related to loan dynamics after default. It is evident that the transition to cure and liquidation final status occurs relatively quickly compared to modification. Furthermore, successful renegotiations are typically granted at a later stage compared to unsuccessful mortgage modifications.

It is therefore crucial to better understand the driving features behind the different post-default outcomes. On top of that, it is also important to distinguish mortgage behaviour after the cease of governmental support (like HAMP) and the effects it yielded on post-default resolutions. Freddie mac loans offer a proper laboratory to address all this questions.

5.3 Empirical Methodology

As our goal is understanding the determinants of post-default outcomes, the modelling approach needs to handle the multinomial nature of the target variable. For this reason, we employ a discrete time proportional hazard model with competing risks, to analyse how loan-, borrower-level and macro variables impact the different results (Been et al. (2013), Chan et al. (2014) and Voicu et al. (2012)).

The explication of the proportional hazard model, alongside alternative modelling approaches and the rationale for favouring the presentation of marginal effects, has already been elaborated in the second empirical chapter. Consequently, we advise the reader seeking additional information to refer to Section 4.3.

The data is first structured in a panel unbalanced form, where each loan performance is monthly tracked from point of default onwards. For this reason, we drop each loan's observations before the point of default, and retain all information at origination that is needed. Next, we define the post-default outcomes of interest. As mentioned in Section 5.2, each mortgage of our sample can transition in any of the following k statuses: *Cure*, *Liquidation*, *Delinquency*, $Successful$ and *Unsuccessful (Failed) Modification.* In line with Been et al. (2013), our reference category is the permanence in a delinquency status. If a loan keeps being delinquent, we retain all observations related to this status. In contrast, all other outcomes are considered as absorbing events for the purpose of our analysis, and we therefore drop any observation after any of these occurrences. In order to separate $Successful$ and *Unsuccessful (Failed) Modification*, we also check the very final status following renegotiation. We therefore flag as *Unsuccessful (Failed) Modification* all those renegotiations that eventually resulted in a *Liquidation*. In any case, we consider the very first transition into modification as a terminal event and, if a loan is re-modified, we do not consider subsequent modifications. Owing to the scarcity of observations, the main analysis is focused on the overall $Modification$ outcome, merging the two sub-categories to mitigate estimate volatility. However, a separate estimation is run by considering the $Modification$ split.

Then, for each of the K possible outcomes, multinomial logistic regression is fitted as per Equation 5.1:

$$ln(\frac{Pr(Y_{it} = k)}{Pr(Y_{it} = K)}) = W_{it,k} \forall k < K \tag{5.1}$$

where:

$$Pr(Y_{it} = k) = \frac{e^{W_{it,k}}}{1 + \sum_{k=1}^{K} e^{W_{it,k}}} \forall k < K \tag{5.2}$$

$$Pr(Y_{it} = K) = \frac{1}{1 + \sum_{k=1}^{K} e^{W_{it,k}}} \forall k = K \tag{5.3}$$

with:

$$\begin{gathered} W_{it,k} = \alpha_k + \sum_{b=1}^{N_b} \beta_{b,k} Loan_{b,i(t)} + \sum_{c=1}^{N_c} \gamma_{c,k} Borrower_{c,i(t)} + \\ \sum_{d=1}^{N_d} \delta_{d,k} State_{d,i} + \lambda_{l,k} Controls_{l,t} \end{gathered} \tag{5.4}$$

or:

$$\begin{gathered} W_{it,k} = \alpha_k + \sum_{b=1}^{N_b} \beta_{b,k} Loan_{b,i(t)} + \sum_{c=1}^{N_c} \gamma_{c,k} Borrower_{c,i(t)} + \\ \sum_{d=1}^{N_d} \delta_{d,k} State_{d,i} + \zeta PolicyPeriod_t + \sum_{b=1}^{N_b} \eta_{b,k} PolicyPeriod_t \times Loan_{b,i(t)} + \\ \sum_{c=1}^{N_c} \theta_{c,k} PolicyPeriod_t \times Borrower_{c,i(t)} + \sum_{d=1}^{N_d} \iota_{d,k} PolicyPeriod_t \times State_{d,i} + \\ \lambda_{l,k} Controls_{l,t} \end{gathered} \tag{5.5}$$

where k denotes one of the defined K outcomes. The subscript t for loan characteristics is in brackets to denote that only some of the characteristics are time dependent.

Amongst the explanatory drivers, *Borrower* includes features indexed with c related to the mortgagor, such as credit score, debt-to-income and number of applicants, while *Loan* include features indexed with b related to the mortgage, such as original loan-to-value, purpose and age of the loan. *Controls* includes macro-sensitive factors, such as 12 month unemployment rate (lagged by 2 years) and interest rate spread, which is the difference between interest rate at origination and Freddie Mac 30Yr mortgage rate. *Controls* also include dummy variables that flag the default period of the mortgage, i.e. if it the loan entered liquidation $Pre-$, $During-$ and $Post-$ HAMP. We consider *State* variability indexed with d by including relevant information related to (a) geographical location, (b) recourse versus non-recourse legislation[7] and (c) judicial versus non-judicial legislation[8]. The multinomial logistic regression has been executed under two distinct configurations, as indicated by Equation 5.4 and Equation 5.5. Equation 5.4 applies to the complete sample, without any differentiation concerning policy periods. Conversely, as per Equation 5.5, the dummy $PolicyPeriod_t$ separates the activation of mortgage payment-relief policy terms taking one of the following values: *Pre-Crisis*, *Crisis* and *Post-Crisis*. The *Crisis* period runs from 2009 until the end of 2016, overlapping with the enactment and dismissal of $HAMP$. This is done on purpose, as this program substantially re-shaped post-default resolutions, in particular for what concerns loan renegotiations. In doing so, we can fully capture the effect of government policy cycles and its effect on each of the explanatory drivers, without restricting our sample to a specific time frame. On the other hand, *Pre-Crisis* is activated from the first observation period until the beginning of HAMP, while *Post-Crisis* captures the years following the dismissal of the program until the end of the observed data. The $PolicyPeriod_t$ changes across observation time and is different from the *Controls* that capture the default period instead. In other words, a loan can default during the enactment from HAMP (hence the control variable would take the value *During-HAMP* throughout the entire observation), but it can continue its permanence

[7] To identify states with non-recourse legislation, we referenced the definition in Nam and Oh (2021).

[8] To identify states with judicial/non-judicial law, we referenced the definition in Ding et al. (2022), who use the classification provided by the National Consumer Law Center (NCLC) (National Consumer Law Center (NCLC) (2022)).

in default and its exit even after the cease of the program. In that case, $PolicyPeriod_t$ would change for the same loan from *Crisis* to *Post-Crisis.* Such approach takes into consideration the dynamic nature of mortgage breaks and their impact on post-default resolutions.

5.4 Results

The results of the multinomial logistic regressions are presented from Table 5.5 through to Table 5.8. As elaborated in Section 5.3, the primary focus is on average marginal effects, not *Relative Risk Ratios*, to accommodate for the non-linearities introduced by the interaction term. However, the *Relative Risk Ratios* are also included, facilitating a more direct comparison of non-interacted terms with existing literature. The first column reports the estimates of the post-modification outcome, labelled as *Cure*, followed by the average marginal effects of *Modification*, and finally, *Liquidation.* The *Delinquency* category is omitted, as it functions as the reference status. As already described in Section 4.4 for continuous variables, results presented in this section will consider a specific, meaningful shift for the variable in question.
Further consideration is required for the observation window, specifically for records following the Covid-19 pandemic (i.e., post-March 2020) which have been removed. This action is necessitated by the distinct consumer behaviour during this period, influenced by the enactment of forbearance measures by the CARES Act (*Coronavirus Aid, Relief, and Economic Security Act, H.R. 748, 116th Cong. (2020)* (2020)). As depicted in Figure 5.3a, the years following the pandemic show a disproportionate share of delinquent and cured borrowers. The challenge arises when differentiating between mortgagors who requested a temporary payment suspension (thus, seemingly in default) and those who were genuinely delinquent. This distinction affects the identification of defaulted mortgages chosen for analysis and the monitoring of post-default behaviour. Given these factors, a conservative approach, which eliminates these observations, is preferred.

The initial focus is directed towards the model delineated in Table 5.5 (and Table 5.6), examining the comprehensive post-default dynamics within the entire observation window and across policy cycles. Initially, we considered a model that was not distinguishing among policy cycles to understand if general trends could be observed. However, we soon found out that the time frame under scrutiny affects borrower behaviour, and market disruptions alter the impact of specific factors on post-default outcomes. Table 5.5 immediately extricates these trends, which will be discussed in the remainder of this section.

In this initial analysis, the $Modification$ outcome is not separated between $Successful$ and $Failed$, but treated as a whole. The objective of this initial comparison is to evaluate the overall validity of the estimations and to draw parallels with preceding work by Been et al. (2013) and Chan et al. (2014), while highlighting at the same time the effects of the different policy periods. This comparison is instrumental in identifying discrepancies arising from the sample utilised, or in confirming consistencies in post-default behaviour within the wider mortgage market. The focus will be on those characteristics shared by both samples, given that either the authors employ a set of neighbourhood features unavailable in our data, as well as on variables not considered in comparative literature.

Starting from continuous variables at origination, it is observed that the "usual suspects" are largely aligned with prior literature, demonstrating both statistical and economic relevance. For instance, the *Credit Score* exhibits a unique pattern, albeit in line with Been et al. (2013): higher scores correspond to a reduced likelihood of modification and an increased probability of liquidation. Upon initial consideration, the observed trend may seem counter-intuitive. However, it is corroborated by both graphical inspection and univariate analysis, the latter of which was conducted in the preliminary stage to examine the relationship between potential predictors and the final outcomes. A plausible explanation for this phenomenon can be found in the distribution of supplementary characteristics, as indicated in Table 5.3 and Table 5.4. Mortgages that have been liquidated or modified are associated with a population that presents a slightly higher risk in terms of *Debt-to-Income*, *Loan-to-Value*, and *Inter-*

est Rate ratios, and these mortgages also constitute a significantly larger proportion of the TPO *Channel*, which is associated to mortgages originated before the Global Financial Crisis without sufficient levels of underwriting scrutiny. These factors may obscure the ultimate influence of the *Credit Score*, highlighting the reality that once a borrower defaults, the *Credit Score* no longer serves as an accurate indicator of risk, while instead other factors gain prominence for lenders when considering support for these borrowers following severe delinquency. Interestingly, the *Credit Score* impact on *Liquidation* and $Modification$ is consistent throughout the policy periods, hence confirming that lenders and servicers view remains unchanged. In addition to our interpretation, recent literature (Albanesi et al. (2022), Adelino et al. (2016), and Ferreira and Gyourko (2015)) also highlights the correlation between prime borrowers (i.e. those with higher credit scores) and elevated default and foreclosure rates, particularly during the Global Financial Crisis, which further corroborates the soundness of the results observed. Pertaining to the influence of the *Credit Score* on $Cure$, we immediately observe that the effect varies over time. As one would expect, higher scores enhance the probability of $Cure$ both before and after the termination of HAMP, which is in full agreement with the findings of Been et al. (2013). On the other hand, the enactment of government support schemes reverts the sensitivity of *Credit Score* on $Cure$ post-default status.

The *Debt-to-Income* ratio exhibits a similar pattern to the *Credit Score*, albeit on different post-default resolutions. Borrowers burdened with high debt relative to their income are less likely to cure, a trend which remains steady across policy cycles, but is more pronounced in the pre-HAMP era. A 10-point increase in *Debt-to-Income* results in a 14 bps decrease in the likelihood of cure before HAMP, compared to 1.4 bps and 6.1 bps during and after the program. The same reasoning applies to $Modification$, as borrowers with higher debt relative to income are more likely to be modified, aligning with the notion that lenders and servicers may seek to alleviate borrowers' financial strain. Specifically, the propensity to modify these mortgages increases during the HAMP period, as a 10-point rise (i.e., from 30 to 40) doubles the modification likelihood during HAMP (12 bps increase), compared with a 5.7 and 4.1 before and after the enacted policy. Both these trends fully align with Been et al. (2013). Interestingly, a higher *Debt-to-Income* results in lower chances of *Liquidation* during the HAMP period, while the contrary is observed outside HAMP window. This emphasises that the introduction of government programs causes a shift in the behaviour of borrowers, lenders, and servicers in addressing post-default resolutions, although the trend reverts to its usual course once federal aid is withdrawn. It is probable that due to the financial stimulus in modifications during HAMP, borrowers managed to avoid foreclosure, although this trend has reversed once the program has been discontinued. Furthermore, the observations on *Debt-to-Income* underline that government policies shielded the most vulnerable borrowers.

Finally, within the set of continuous variables at origination, the *Loan-to-Value* ratio is entirely consistent with existing literature, as it enhances the likelihood of $Modification$ and *Liquidation*, whilst reducing the probability of curing. *Loan-to-Value* marginal effects remains steady across policy cycles, highlighting that borrower exposure over property appraisal value unfolds a highly predictive and strong pattern that is universally observed despite mortgage market breaks. It is important to acknowledge the constraints associated with employing the *Loan-to-Value* ratio at origination compared to its updated counterpart. Specifically, the *Loan-to-Value* ratio at origination fails to account for the current market value of the property or the outstanding balance of the mortgage, as discussed in Sections 4.2 and 5.2. Consequently, the impact of the *Loan-to-Value* at origination on post-default outcomes may be less significant than that of its updated version, which more accurately reflects the borrowers' risk exposure. However, utilising the *Loan-to-Value* at origination serves as a mitigating factor by limiting potential estimation errors that could arise from adjusting the property value using the State-level Housing Price Index (HPI), especially given the small sample size that could result in outliers disproportionately influencing the final estimates.

Consistent trends are observed for *Loan Age*, *Balance*, *Time in Default*, and *Interest Rate Spread*. Specifically, *Loan Age* and *Balance* correlate with the findings of Been et al. (2013), suggesting that more seasoned mortgages are more likely to be cured and modified, and less likely to be liquidated. This trend is intuitive; older mortgages, having progressed significantly in their repayment schedule, are more easily cured and more attractive for modification, as the probability of a successful outcome increases. Conversely, loans with larger balances are less likely to cure or be liquidated, making modification a more favourable option. In particular, the impact of *Balance* on post-default outcomes reveals a remarkably stable trend across cycles. As one might expect, higher balances are less likely to cure, due to the substantial amount, and less likely to be liquidated, as lenders and servicers aim to offer an alternative to avoid substantial loss. On the contrary, mortgages with higher balances are more likely to undergo modification, as a strategy from lenders to minimise potential high losses. Interestingly, the marginal effects for $Modification$ remain stable and economically significant over time. A \$15k increase in balance raises the probability of modification by 61 bps before, 94 bps during, and 68 bps after the crisis. A noteworthy economic impact is also observed on $Liquidation$, as the same \$15k increase results in a decrease of 43 bps, 28 bps, and 95 bps across the three breaks analysed.

Another interesting pattern emerges when considering *Time Since Default*. The post-default outcomes appear influenced by the specific period under examination. Prior to the enactment of HAMP, an extended duration in default heightened the likelihood of cure, conversely diminishing the probabilities of liquidation and modification. However, following the introduction of HAMP, and persisting even after its cessation, an extended duration in default inversely impacts post-default outcomes, reducing the probability of cure while escalating the odds of modification and liquidation. This shift likely underscores that, before the crisis, borrowers would persist in a default state, striving for cure at all costs rather than risk liquidation, as modifications were anything but commonplace and were implemented as promptly as possible (consistent with Been et al. (2013), who examine the same time period). Once renegotiations became more prevalent, perhaps due to increased volumes, the struggle for self-cure was alleviated by modifications, which evolved into a more frequently employed tool to assist mortgagors in extricating themselves from lingering into default.

Lastly, the *Interest Rate Spread* deserves attention. Higher spreads lead to lower cure rates post-first default and lower chances of modification, in accordance with economic intuition. There may be several reasons for this. Firstly, modifying a loan with a high interest rate, relative to the market rate, may be deemed less profitable. Secondly, a high spread may conceal the borrower's inherent risk, making it less suitable for modification. As a result, borrowers with higher spreads are more likely to be liquidated upon entering default status. The dummy variables *During-HAMP* and *Post-HAMP* capture the effect of default period on post-default resolution. We observe a consistency in the impact on *Liquidation* and $Modification$, as both periods highlight an increased propensity in modifying mortgages and in reducing foreclosure, compared with loans that defaulted before the enactment of HAMP. On the other hand, mortgages that defaulted during $HAMP$ hold a lower probability of curing, possibly because it is more likely to obtain a modification instead.

Beyond the variables in common with the research of Been et al. (2013) and Chan et al. (2014), our study contributes a novel perspective by incorporating additional determinants of post-default resolutions, which are overlooked in previous literature. Specifically, as Been et al. (2013) and Chan et al. (2014) concentrate on New York, they are unable to examine the impact of *Judicial* and *Non Recourse* laws on post-default outcomes, given the homogeneity of their sample in this regard. Utilising nationally representative data enables us to provide further insight. Furthermore, we include variables such as *Joint* and *Mortgage Insurance*, which effectively clarify mortgagors behaviour and are absent in existing literature.

When examining the influence of state laws on post-default resolutions, two noteworthy trends emerge. Commencing with *Judicial*, Table 5.5 indicates that mortgages subject to such legislation tend to exhibit lower probabilities of *Cure*, $Modification$ and *Delinquency*. These trends remain consistent regardless of the policy cycle under scrutiny. As identified in Phillips and VanderHoff (2004), mortgages in *Judicial* states benefit from court involvement in the foreclosure process, which can significantly decelerate the transition from a delinquency status to any other potential post-default resolution. As a result, we observe that *Judicial* laws reduce the probability of entering any post-default outcome. Conversely, mortgages in *Non Recourse* states demonstrate an interesting trend, contingent on the specific mortgage cycle. While mortgages in non-recourse states are more likely to be cured or modified and less likely to enter liquidation during the pre- and post-crisis periods, an entirely opposite trend is evident during the active years of the HAMP policy. A plausible explanation is provided by the research of Nam and Oh (2021), who discovered that the impact of non-recourse laws influenced the issuance of highly leveraged mortgages in the years preceding the pandemic. Given the significant drop in house prices in 2008, these mortgages were likely underwater, nearly impossible to cure or modify due to their leverage, and were probably liquidated. This aligns with Ghent and Kudlyak (2011), who determined that the sensitivity to recourse laws is significant when borrowers are in negative equity and/or the property's appraisal value is high. Despite the authors' focus on the propensity to default, their findings supplement the results we obtain. Outside the crisis period, borrowers in *Non Recourse* states may exhibit strategic behaviour as their decision to default could be motivated by the prospect of securing improved contractual terms, given that lenders cannot claim other assets to compensate for the loss and may be inclined to renegotiate the loan to minimise the loss.

The influence of HAMP on post-default resolutions is also evident in *Joint* mortgages. Logically, loans supported by multiple borrowers are more likely to be cured and modified, as household income is typically higher when more members contribute, as shown in Table 5.5. However, it is also evident that this characteristic carries more weight outside the period of policy intervention. For instance, joint applications augment the chances of cure by 45 bps and 13 bps before and after the crisis, respectively. However, during the implementation of the Home Affordable Modification Program (HAMP), we note the smallest contribution, with a 10 bps increase. Similarly, *Joint* borrowers had marginally higher odds of modification either pre- or post-HAMP, with an increase of 10 bps and 27 bps respectively, compared to 6 bps during the crisis. On the other hand, the crisis years and government programs appear to influence the effect of *Joint* borrowing on *Liquidation*, similarly to what happens with *Credit Score* and *Debt-to-Income*. Indeed, we note that joint borrowers are less likely to be liquidated after default outside the HAMP period (-5.2 and -2.6 bps respectively), whereas the reverse is seen during HAMP, with a 6 bps increase in liquidation probability. The preliminary conclusion that pertains all post-default outcomes is that defaulted mortgages, which were subsequently modified, cured, or liquidated under HAMP, benefited from a government stimulus that blurred those characteristics typically associated with virtuous behaviour.

The behaviours of *Purchase* and *Non-cash out refinance* consistently align in terms of their propensity to *Cure* and *Modification*, irrespective of the mortgage market cycles. Finally, *Mortgage Insurance* also displays a consistent behaviour across policy cycles. With the sole exception of *Liquidation* post-Crisis, mortgages with default insurance seem to outperform those without, demonstrating higher chances of modification and lower likelihood of liquidation. This likely reflects the comfort of lenders/servicers in being partially protected in adverse events, or it may be attributed to the financial position of the borrower who must also pay the mortgage insurance premium to maintain their LTV ratio. The occupancy predictor reveals an interesting pattern for *Primary* and *Second Home* types. Mortgages occupied as main residences demonstrate consistent behaviour across policy cycles, particularly regarding *Liquidation* and *Modification*, where decreased and increased likelihoods of entering such statuses are observed, respectively. This aligns with economic intuition and corroborates Voicu et al. (2012) findings, as this occupancy type underscores the combined effect of borrowers' willingness to retain their homes and the protection granted by policymakers to assist these homeowners. For instance, the Home Affordable Modification Program (HAMP) was initially only granted to mortgages backing a primary occupancy, although such attention was evident even prior to this. Similarly, a consistent positive impact of *Primary* occupancy is observed on *Cure*, with the sole exception of the Post-Crisis period, as these mortgagors also strive to exit default through their own means to continue residing in their main property. Conversely, *Second Home* mortgages bear the impact of market cycles on post-default behaviour. Following the introduction of HAMP, *Second Home* mortgages are more likely to be modified and less likely to be liquidated, whereas the opposite behaviour was recorded previously. This shift underscores the positive effect of government policies in extending consumer protection beyond conventional categories. Lastly, mortgages originated through *Third Party Origination* (TPO) exhibit a consistent reduced likelihood of curing across all policy periods. It's crucial to acknowledge the correlation between third-party origination loans and their issuance date, as discussed in Section 5.2. These loans often lack comprehensive documentation and full transparency, which aligns with their persisting risky profile and the difficulty of exiting default status with a positive outcome such as cure.

A concluding observation pertains to the models that distinguish $Successful$ from $Failed$ modifications, presented in Table 5.7 and Table 5.8. The marginal effects of $Cure$ and *Liquidation* remain nearly identical, thereby enabling us to focus solely on the variations in loan-, borrower-, and state-characteristics influencing $Modification$ outcomes, where we observe relevant evolutionary patterns for $Successful$ and $Failed$ modifications. Nonetheless, it is crucial to acknowledge that *Failed Modifications* exhibit lower volumes than their $Successful$ counterparts. Consequently, when separating the different policy cycles, some variables lose their statistical significance. Our discussion will be thus confined to those most relevant that retain statistical significance.

Looking at Table 5.7, we promptly discern the characteristics that effectively differentiate between the two modification outcomes, as opposed to those that do not considerably impact borrowers' post-modification behaviour. For instance, *Credit Score* and *Debt-to-Income* appear to exacerbate the earlier noted trends, whereas the influence of *Loan-to-Value* fluctuates over time. In fact, *Loan-to-Value* initially exerts a stronger impact prior/during to the introduction of HAMP by significantly differentiating failed modifications compared to successful ones. Such effect is then balanced off following HAMP cessation.

Joint borrowers and *Primary* occupancy maintain their intuitive impact over time, albeit with varying intensities. Most notably, *Joint* borrowers drive a virtuous behaviour, as they exhibit a higher probability of achieving a successful modification and a lower probability of failure. As highlighted in the analysis absent $Modification$ split, the impact of *Joint* applicants enhances the probability of $Successful$ modification by 22 bps and 25 bps pre and post-crisis respectively, whereas during the HAMP period it diminishes to 7.2 bps. A similar observation applies to $Failed$ modifications, with *Joint* borrowers being 3.5 bps and 2.1 bps less inclined to enter such status outside of HAMP implementation, while its effect is virtually negligible during the program's active period (0.8 bps decrease). Comparable consistency is noted for *Primary* occupancy, a factor that positively influences $Successful$ modifications across all periods, and to a lesser degree impacts $Failed$ ones.

Other variables that effectively distinguish renegotiations across policy cycles include *Loan Age*, *Time since Default* and *Balance*. Seasoned mortgages have a higher likelihood of successful modification, potentially due to their advanced repayment status, which subsequently renders the loan sustainable post-renegotiation. On the other hand, the more advanced the repayment schedule, the less likely a mortgage will be liquidated following modification across all policy cycles. *Time since Default* also exhibits a strong relationship with failed modifications, as a longer permanence in default lowers the probability of a negative post-modification outcome. Most likely, this can be attributed to a ruthless decision from lenders/servicers in granting modification terms that are not adequate to effectively help the borrower. Interestingly, it is reaffirmed that higher balances precipitate an increase in positive modifications throughout the entire cycle, while their relevance on $Failed$ modifications is less consequential.

Lastly, macroeconomic drivers also assist in differentiating the two modification outcomes. As expected, adverse economic environments, evidenced by rising unemployment, negatively impact $Successful$ modifications while increasing the likelihood of adverse post-modification outcomes. Likewise, higher spread yields lower chances of achieving a positive modification outcome. These borrowers are likely unable to afford the mortgage despite the reduction in payments, given the higher starting point.

5.5 Conclusions

This research scrutinises the consequences of post-default scenarios and their determining factors, taking into account a variety of loan-, borrower-, and state-specific attributes. A comprehensive dataset of Freddie Mac mortgages over a two-decade period is utilised to probe post-default resolutions, encapsulating the impacts of disruptions in the mortgage market triggered by the Global Financial Crisis and the mortgage-related schemes implemented by the US government. The post-default outcomes under investigation include the borrower's cure, modification, and liquidation.

The analysis initially corroborates previous findings, demonstrating the effectiveness of particular determinants in distinguishing post-default outcomes. The data employed for this analysis, relating to GSE securitised mortgages, aids in generalising prior results that were solely based on subprime mortgages or mortgages within a specific jurisdiction. For instance, the significance of Loan-to-Value, mortgage balance, and loan age in influencing post-default resolutions is affirmed.

Secondly, we contribute to extant literature by introducing unexplored variables, such as those relating to specific state laws or borrower attributes. We ascertain that judicial laws decelerate the transition from delinquency for all possible post-default outcomes, whereas recourse states yield varied effects depending on the market cycle under consideration. Furthermore, we discern that joint borrower and insured loans considerably assist borrowers in circumventing liquidation and in positively exiting delinquency via cure or modification.

Thirdly and most significantly, we contribute to the current literature by emphasising how disruptions in the mortgage market influence the post-default outcomes of borrowers and lenders. Specifically, we highlight that government-introduced policies intended to aid financially distressed borrowers can blur the factors typically useful in detecting post-default behaviour. In certain instances, the impact is confined to the period of interest, while in others it triggers a permanent change. This carries substantial implications for both policy and risk management perspectives, warranting careful consideration by risk managers since the modelling period utilised can significantly influence the accurate prediction of specific outcomes.

Figure 5.1: Mortgage Defaults by State

The Graph displays the distribution of defaulted mortgages by States across the entire sample. The sample covers Single-Family residential mortgages originated from February 1999 to February 2022 and securitised by Freddie Mac. The figure displays all defaulted mortgages made available in Freddie Mac database.

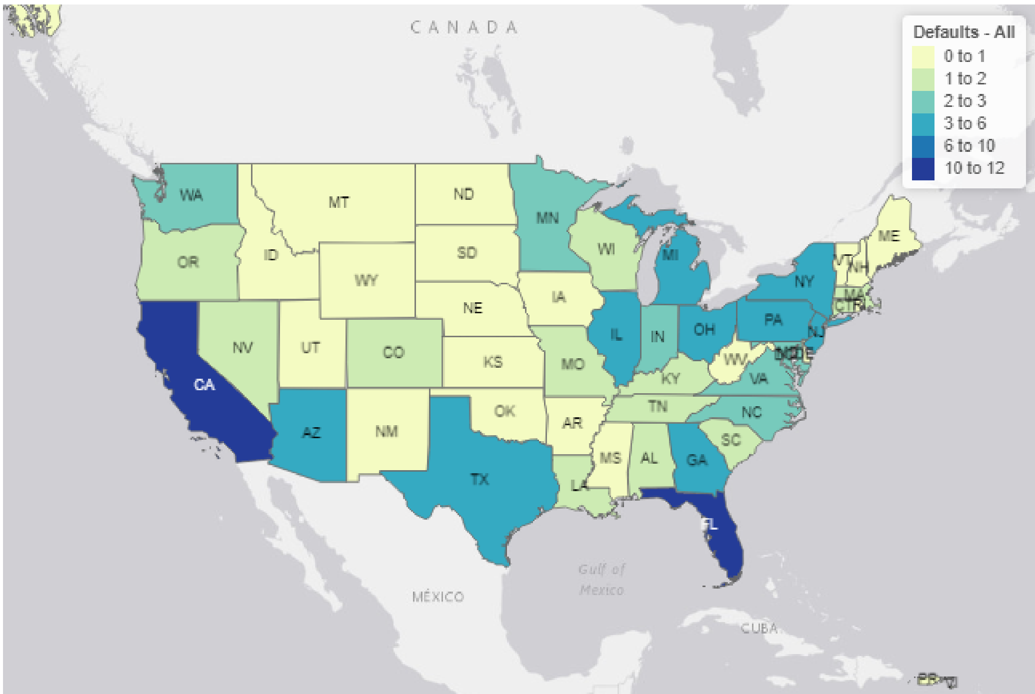
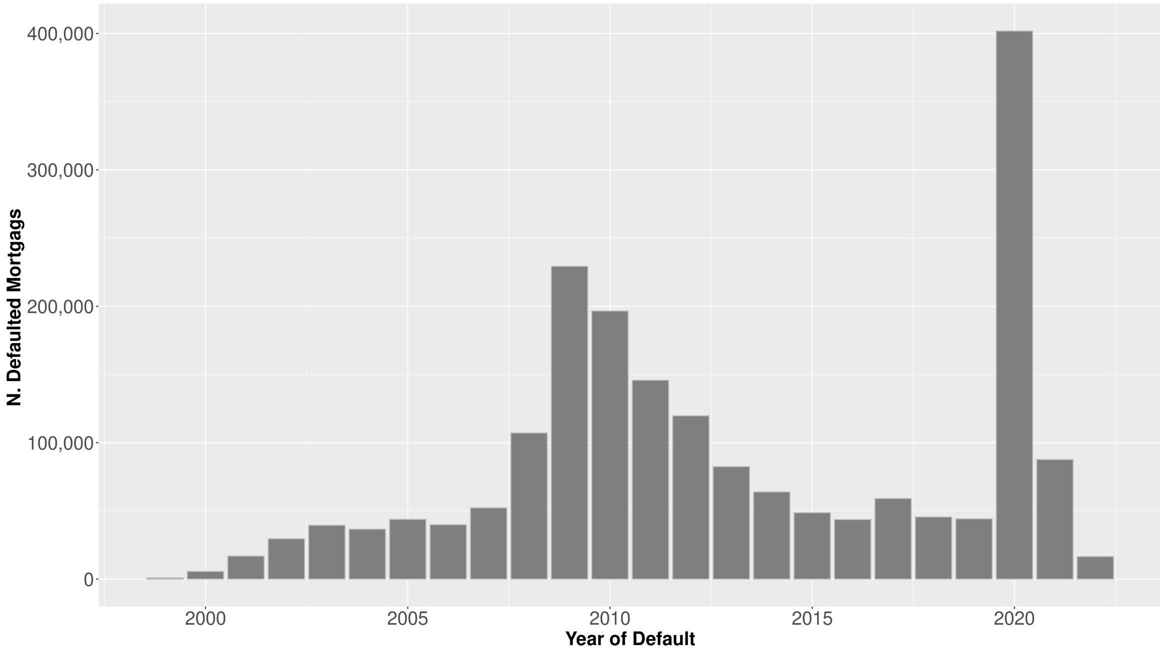
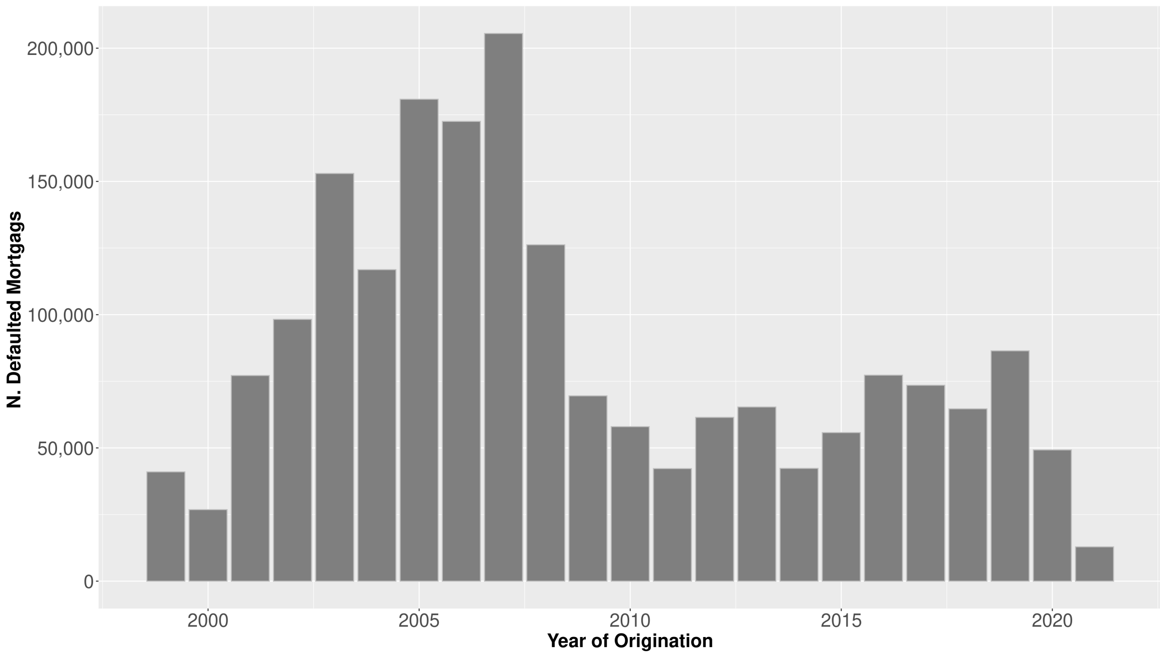


Figure 5.2: Mortgage Defaults by Year of Default and Year of Origination

The Graph displays the number of first default occurrences (a) by year of default and (b) by year of origination.



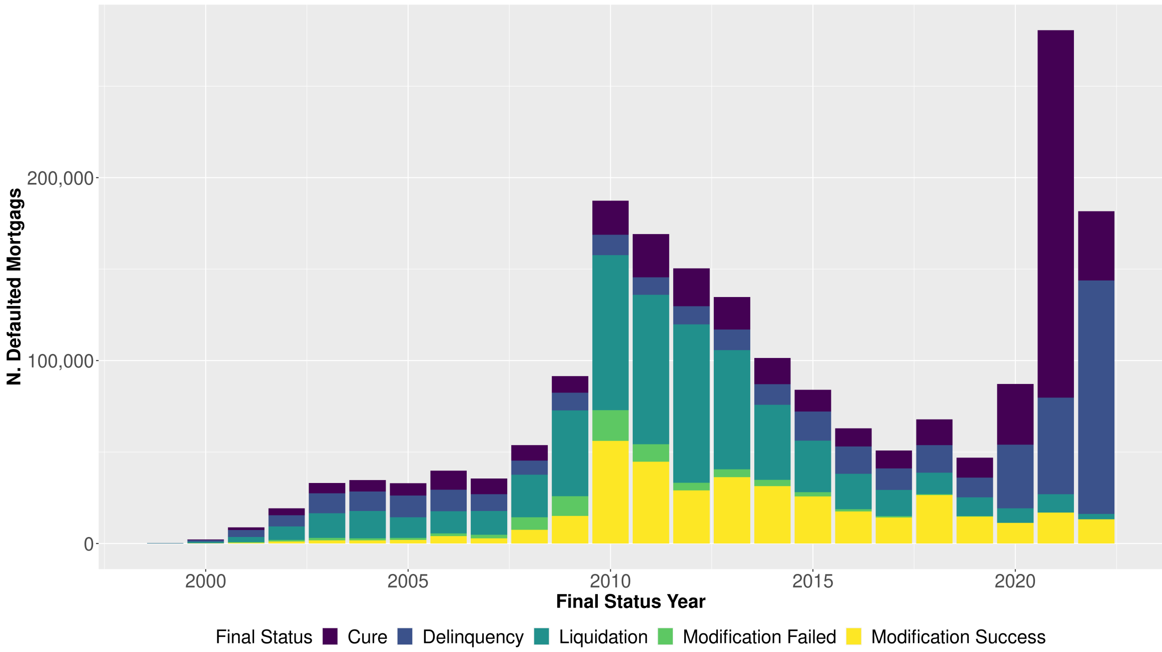
(a)



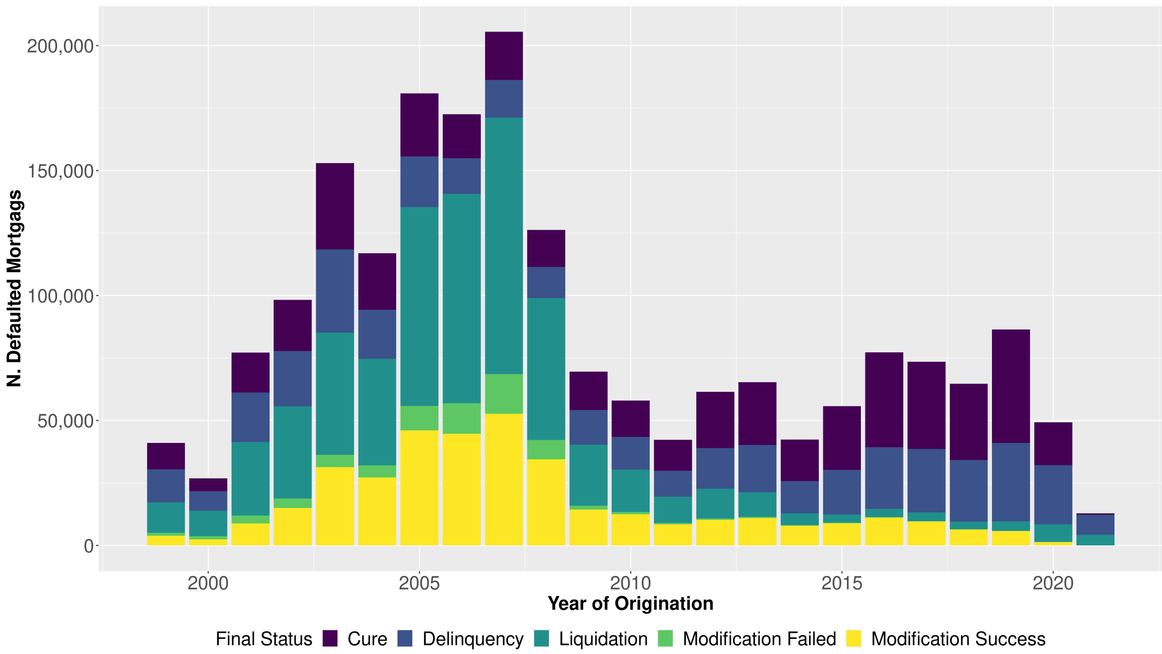
(b)

Figure 5.3: Mortgage Final Status by Last Observation Year and Year of Origination

The Graph displays the distribution of mortgage final status by (a) last observation year and (b) year of origination across the entire sample. The final outcome can take one of the following values: *Cure*, *Delinquent*, *Liquidation*, *Successful* and *Failed Modification*.



(a)



(b)

Table 5.1: Mortgage Sample Characteristics at Default: Categorical

The Table reports percentage distribution of property and borrower types by year of default: *First time home buyer*; *Occupancy*: Investment (Inv), Primary Home(Pr), Second Home (Sec); Origination *Channel*: Broker (Brok), Correspondent (Corr), Retail (Ret), TPO Not Specified (TPO); *Property Type*: Condominium (CO), Co-op (CP), Manufactured House (MH), Planned Unit Development (PU), Single-Family (SF); *Purpose*: Cash-out Refinance (C), No Cash-out Refinance (N), Purchase (P); *Number of Borrowers*: Single (S), Joint (J).

		First Time Buyer		Occupancy			Channel				Property					Purpose			N.Borrowers	
Year	N.Defaults	No	Yes	Inv	Pr	Sec	Brok	Corr	Ret	TPO	CO	CP	MH	PU	SF	C	N	P	S	J
1999	886	89.7%	10.3%	5.5%	91.1%	3.4%	0.0%	0.0%	44.5%	55.5%	6.0%	0.1%	0.5%	5.9%	87.6%	24.8%	37.1%	38.0%	57.2%	42.8%
2000	5,613	86.9%	13.1%	4.4%	93.6%	2.0%	0.0%	0.0%	41.0%	58.9%	5.4%	0.0%	0.9%	6.8%	86.8%	23.9%	29.2%	46.9%	58.5%	41.5%
2001	16,876	87.9%	12.1%	5.3%	92.8%	1.9%	0.1%	0.0%	38.5%	61.4%	5.3%	0.0%	1.2%	7.1%	86.4%	24.9%	29.0%	46.1%	56.7%	43.3%
2002	29,577	89.7%	10.3%	7.1%	91.3%	1.7%	0.0%	0.0%	33.3%	66.6%	4.3%	0.0%	1.4%	6.5%	87.7%	27.6%	33.7%	38.7%	59.8%	40.2%
2003	39,473	91.1%	8.9%	6.6%	91.5%	1.9%	0.0%	0.0%	35.0%	64.9%	3.9%	0.0%	1.5%	6.5%	88.0%	30.6%	36.2%	33.2%	57.1%	42.9%
2004	36,598	91.6%	8.4%	5.7%	92.5%	1.8%	0.0%	0.0%	38.2%	61.8%	3.7%	0.0%	2.2%	6.2%	87.8%	31.3%	38.0%	30.7%	57.5%	42.5%
2005	43,819	93.2%	6.8%	5.2%	92.9%	1.9%	0.0%	0.0%	38.2%	61.7%	3.3%	0.1%	2.2%	5.5%	89.0%	33.4%	38.9%	27.7%	56.3%	43.7%
2006	39,883	92.1%	7.9%	4.6%	91.2%	4.2%	0.0%	0.0%	41.8%	58.1%	7.0%	0.1%	2.0%	7.0%	83.9%	34.4%	35.6%	30.0%	56.9%	43.1%
2007	52,244	91.1%	8.9%	4.2%	93.2%	2.7%	0.0%	0.0%	39.2%	60.8%	5.1%	0.1%	2.1%	8.1%	84.6%	37.7%	30.8%	31.6%	58.7%	41.3%
2008	107,124	90.2%	9.8%	5.9%	90.2%	3.9%	0.4%	0.3%	37.8%	61.5%	7.4%	0.1%	1.6%	11.5%	79.4%	38.7%	26.1%	35.2%	59.2%	40.8%
2009	229,320	90.7%	9.3%	5.8%	90.6%	3.6%	2.1%	1.9%	38.3%	57.7%	7.5%	0.1%	1.3%	13.1%	78.1%	41.3%	25.8%	32.8%	56.1%	43.9%
2010	196,539	90.7%	9.3%	5.8%	90.6%	3.5%	3.1%	3.2%	41.7%	52.1%	7.9%	0.1%	1.4%	13.3%	77.3%	40.8%	27.2%	32.0%	54.9%	45.1%
2011	145,765	91.1%	8.9%	6.4%	89.8%	3.8%	3.3%	5.2%	45.1%	46.4%	8.4%	0.1%	1.4%	13.2%	76.8%	38.3%	30.8%	30.9%	55.1%	44.9%
2012	119,710	91.4%	8.6%	6.2%	90.1%	3.7%	3.6%	5.9%	50.2%	40.3%	8.6%	0.2%	1.6%	12.5%	77.2%	35.7%	35.9%	28.4%	54.8%	45.2%
2013	82,440	92.0%	8.0%	6.2%	90.3%	3.5%	3.9%	7.4%	54.4%	34.3%	7.9%	0.2%	1.5%	11.3%	79.0%	33.2%	41.4%	25.5%	56.8%	43.2%
2014	63,910	92.4%	7.6%	6.7%	90.4%	2.9%	4.0%	9.3%	58.7%	28.0%	7.1%	0.2%	1.5%	10.6%	80.5%	29.9%	46.6%	23.5%	58.5%	41.5%
2015	48,658	92.0%	8.0%	6.8%	90.2%	2.9%	4.4%	11.7%	61.0%	22.9%	7.1%	0.3%	1.5%	11.1%	80.0%	27.7%	48.6%	23.7%	60.7%	39.3%
2016	43,657	90.4%	9.6%	7.1%	90.1%	2.8%	5.2%	13.9%	62.1%	18.8%	6.6%	0.2%	1.5%	12.5%	79.2%	25.6%	48.2%	26.3%	62.8%	37.2%
2017	59,090	86.4%	13.6%	6.6%	90.8%	2.6%	7.2%	17.9%	62.1%	12.7%	6.7%	0.1%	1.0%	21.5%	70.6%	25.1%	41.8%	33.1%	62.5%	37.5%
2018	45,538	84.7%	15.3%	6.4%	91.0%	2.6%	6.8%	19.3%	62.0%	11.9%	7.0%	0.2%	1.2%	16.9%	74.7%	25.1%	39.8%	35.0%	65.2%	34.8%
2019	44,197	80.8%	19.2%	6.1%	91.6%	2.3%	7.1%	23.0%	60.9%	9.0%	6.9%	0.2%	1.4%	16.8%	74.7%	24.4%	35.0%	40.6%	66.9%	33.1%
2020	401,781	79.4%	20.6%	9.1%	88.0%	2.9%	9.7%	32.3%	55.4%	2.5%	8.0%	0.2%	0.5%	23.9%	67.4%	22.1%	33.4%	44.4%	59.3%	40.7%
2021	87,658	79.2%	20.8%	6.2%	91.0%	2.8%	10.4%	27.7%	59.0%	3.0%	8.5%	0.2%	0.8%	21.8%	68.7%	22.7%	35.3%	42.1%	65.9%	34.1%
2022	16,503	78.0%	22.0%	4.8%	92.4%	2.8%	10.6%	28.0%	58.9%	2.6%	8.3%	0.2%	1.2%	20.4%	69.8%	24.0%	32.2%	43.7%	68.6%	31.4%

Table 5.2: Mortgage Sample Characteristics at Default: Continuous

The Table reports 5^{th} quantile, mean, standard deviation and 95^{th} quantile of *Credit Score*, *Debt-to-Income*, *Interest rate* and *Loan-to-Value* by year of default. *Credit Score* is borrower's Credit Score at origination. *Debt-to-Income* is the sum of borrower's monthly debt payments, including housing expenses that incorporate mortgage payment, divided by total monthly income used for underwriting. *Interest rate* is the contractual interest rate at origination. *Loan-to-Value* is the ratio between *Balance* and *PropertyPrice* at origination. *Balance* is the balance at origination.

	Credit Score				Debt-to-Income				Interest Rate				Loan-to-Value				Balance			
Year	q5	Mean	Sd	q95	q5	Mean	Sd	q95	q5	Mean	Sd	q95	q5	Mean	Sd	q95	q5	Mean	Sd	q95
1999	549	658.45	63.50	769.9	14.0	32.17	11.54	52.0	6.5	7.20	0.56	8.3	47.0	76.71	15.20	95.0	39,250	105,556	55,296	221,000
2000	563	654.51	56.00	754.85	17.0	34.82	10.93	53.0	6.6	7.76	0.88	9.3	50.0	79.29	14.73	95.0	38,000	105,250	52,443	210,000
2001	566	654.66	56.24	757	17.0	35.54	10.87	53.0	6.8	7.95	0.87	9.5	50.0	79.70	14.41	95.0	40,000	112,679	57,181	230,000
2002	556	649.48	58.97	754	17.0	35.55	10.89	52.0	6.5	7.63	0.81	9.0	53.0	80.23	13.44	95.0	40,000	112,333	58,672	234,000
2003	564	654.40	58.69	758	16.0	35.63	11.11	53.0	5.9	7.20	0.83	8.6	52.0	79.57	13.75	95.0	41,000	116,750	62,225	244,000
2004	574	658.93	55.71	757	17.0	35.80	11.10	53.0	5.4	6.81	0.91	8.4	53.0	79.78	13.45	95.0	41,000	113,967	61,457	241,000
2005	585	668.04	55.76	767	16.0	35.52	11.51	54.0	5.1	6.37	0.90	8.0	50.0	77.84	14.07	95.0	41,000	116,838	63,449	248,000
2006	587	669.48	56.10	769	16.0	36.12	11.67	55.0	5.1	6.24	0.79	7.8	48.0	77.00	14.44	95.0	42,000	126,191	71,015	272,000
2007	589	669.79	54.60	766	17.0	37.31	11.65	57.0	5.3	6.25	0.71	7.5	49.0	77.14	14.32	95.0	45,000	141,720	81,098	306,000
2008	595	676.63	54.12	771	19.0	38.86	11.71	58.0	5.4	6.32	0.65	7.4	52.0	78.26	13.64	97.0	52,000	172,852	94,630	360,000
2009	602	685.83	53.68	777	20.0	39.78	11.63	59.0	5.4	6.27	0.60	7.3	52.0	77.32	13.12	95.0	60,000	192,054	97,660	380,000
2010	608	693.87	54.51	783	19.0	39.62	11.70	59.0	5.1	6.17	0.61	7.1	50.0	76.59	13.53	95.0	60,000	187,636	96,991	376,000
2011	610	699.05	55.84	788	19.0	38.90	11.79	59.0	4.9	6.06	0.67	7.1	49.0	76.71	14.33	95.0	57,000	180,520	95,706	368,000
2012	611	703.04	56.93	792	18.0	38.19	11.66	58.0	4.6	5.90	0.78	7.0	48.0	77.25	15.53	100.0	56,000	178,662	96,709	369,000
2013	607	700.43	57.98	792	18.0	37.77	11.55	57.0	4.1	5.73	0.90	7.0	48.0	78.56	17.86	106.0	52,000	168,988	95,679	360,000
2014	604	699.76	59.21	793	17.0	37.08	11.49	56.0	3.9	5.49	0.99	7.0	46.0	79.25	19.42	114.0	50,000	160,214	93,767	352,000
2015	603	700.80	59.89	794	17.0	36.79	11.21	55.0	3.8	5.32	1.02	6.9	45.0	79.46	20.16	116.0	49,000	158,442	94,774	355,150
2016	603	700.73	59.80	795	17.0	36.38	10.87	53.0	3.6	5.14	1.03	6.9	44.0	79.23	20.14	114.0	49,000	160,752	98,453	367,000
2017	609	702.11	57.67	793	19.0	37.11	9.86	51.0	3.5	4.86	1.00	6.8	45.0	79.13	19.35	110.0	53,000	175,644	104,337	388,000
2018	614	703.42	57.16	795	19.0	37.00	9.84	50.0	3.5	4.82	0.97	6.6	44.0	78.53	19.02	105.0	51,000	176,075	108,069	396,000
2019	620	704.11	56.01	796	20.0	37.26	9.41	50.0	3.5	4.79	0.92	6.5	44.8	78.74	18.47	101.0	52,000	184,831	115,805	413,000
2020	637	722.00	50.86	798	22.0	38.19	8.53	49.0	3.3	4.37	0.76	5.8	45.0	77.87	17.23	97.0	75,000	246,988	133,061	484,000
2021	634	720.40	51.95	800	21.0	37.39	8.74	49.0	2.8	4.06	0.96	5.9	45.0	77.52	17.30	97.0	65,000	231,296	137,311	496,000
2022	634	716.11	51.62	799	21.0	37.29	8.72	49.0	2.6	3.82	0.98	5.8	43.0	76.59	17.51	97.0	65,000	234,184	145,114	512,000

Table 5.3: Mortgage Sample Characteristics at Default by Resolution Outcome: Categorical

The Table reports percentage distribution of property and borrower types by final status. The first row of each category represents the percentage column distribution. The second row, with numbers in brackets, represents the percentage row distribution. *Loan Purpose*: Cash-out Refinance (C), No Cash-out Refinance (N), Purchase (P); Origination *Channel*: Broker (Brok), Correspondent (Corr), Retail (Ret), TPO Not Specified (TPO); *First time home buyer*; *Number of units*; *Occupancy*: Investment (Inv), Primary Home(Pr), Second Home (Sec); *Property Type*: Condominium (CO), Co-op (CP), Manufactured Housing (MH), Planned Unit Development (PU) and Single-Family (SF); *Number of Borrowers*: Single (S), Joint (J). The sample includes 1,453,556 mortgages observed from 1999 to 2022.

Variable	Categories	Cure	Delinquency	Liquidation	Modif. Failed	Modif. Success
Loan Purpose	C	27.6%	29.2%	32.6%	37.3%	37.6%
		(21.5%)	(19.7%)	(32.0%)	(4.2%)	(22.6%)
	N	35.1%	34.7%	32.4%	28.4%	33.4%
		(25.9%)	(22.1%)	(30.1%)	(3.0%)	(19.0%)
	P	37.3%	36.0%	35.0%	34.3%	29.0%
		(26.7%)	(22.3%)	(31.5%)	(3.5%)	(16.0%)
Channel	Brok	6.3%	6.4%	2.7%	2.2%	4.0%
		(33.8%)	(29.6%)	(18.4%)	(1.6%)	(16.6%)
	Corr	20.6%	18.3%	4.3%	2.9%	8.8%
		(42.0%)	(32.2%)	(11.1%)	(0.8%)	(13.8%)
	Ret	52.6%	52.8%	45.1%	37.8%	46.7%
		(26.8%)	(23.2%)	(28.9%)	(2.8%)	(18.4%)
	TPO	20.5%	22.4%	47.8%	57.1%	40.5%
		(14.7%)	(13.9%)	(43.2%)	(5.8%)	(22.4%)
First Time Home buyer	N	84.7%	85.8%	89.8%	88.4%	89.2%
		(24.0%)	(21.0%)	(32.0%)	(3.6%)	(19.5%)
	Y	15.3%	14.2%	10.2%	11.6%	10.8%
		(30.4%)	(24.4%)	(25.5%)	(3.3%)	(16.5%)
Number of Units	1	96.5%	96.8%	96.9%	98.2%	97.2%
		(24.7%)	(21.4%)	(31.2%)	(3.6%)	(19.2%)
	2	3.5%	3.2%	3.1%	1.8%	2.8%
		(27.9%)	(21.9%)	(31.0%)	(2.1%)	(17.1%)
Occupancy Status	Inv	7.2%	6.5%	9.1%	2.8%	2.9%
		(26.9%)	(20.7%)	(42.5%)	(1.5%)	(8.3%)
	Pr	89.8%	90.8%	86.3%	95.5%	95.4%
		(24.7%)	(21.5%)	(29.8%)	(3.7%)	(20.2%)
	Sec	3.0%	2.7%	4.6%	1.7%	1.6%
		(23.6%)	(18.7%)	(45.8%)	(1.9%)	(10.0%)
Property Type	CO	6.6%	7.2%	9.8%	5.1%	5.0%
		(22.3%)	(20.9%)	(41.3%)	(2.5%)	(13.1%)
	CP	0.2%	0.2%	0.1%	0.1%	0.1%
		(35.7%)	(28.5%)	(21.1%)	(1.4%)	(13.3%)
	MH	0.9%	0.8%	1.9%	1.7%	1.1%
		(17.6%)	(14.5%)	(46.4%)	(4.7%)	(16.7%)
	PU	17.5%	17.0%	12.4%	12.6%	14.4%
		(28.8%)	(24.2%)	(25.7%)	(3.0%)	(18.3%)
	SF	74.8%	74.8%	75.9%	80.5%	79.4%
		(24.3%)	(21.0%)	(31.1%)	(3.7%)	(19.9%)
Number of Borrowers	S	56.6%	61.0%	60.5%	58.2%	54.6%
		(24.0%)	(22.3%)	(32.3%)	(3.5%)	(17.9%)
	J	43.4%	39.0%	39.5%	41.8%	45.4%
		(25.9%)	(20.1%)	(29.6%)	(3.6%)	(20.9%)

Table 5.4: Mortgage Sample Characteristics at Default by Resolution Outcome: Categorical

The Table reports 5^{th} quantile, mean, standard deviation and 95^{th} quantile of *Credit Score*, *Debt-to-Income*, *Loan-to-Value*, *Debt-to-Income*, *Interest rate*, *Balance*, *Loan Age*, *Remaining Term* and *Loan Age* by final status. *Credit Score* is borrower's Credit Score at origination. *Loan-to-Value* is the ratio between outstanding *Balance* and *PropertyPrice* at time of origination. *Debt-to-Income* is the sum of borrower's monthly debt payments, including housing expenses that incorporate mortgage payment, divided by total monthly income used for underwriting. *Interest rate* is the contractual interest rate at origination. *Balance* is the underwritten mortgage balance at origination. *Loan Age* is the age of the loan in months at time of the final event. *Remaining Term* is the number of months to maturity. *Time Since Default* represents the number of months from first default and final status. The sample includes 1,453,556 mortgages observed from 1999 to 2022.

Variable	Statistic	Cure	Delinquency	Liquidation	Modif. Failed	Modif. Success
Credit Score	Mean	704.72	704.79	697.24	670.46	684.44
	Sd	57.87	58.14	57.73	54.40	55.98
	q5	610.00	610.00	605.00	588.00	597.00
	Median	706.00	705.00	697.00	667.00	683.00
	q95	794.00	795.00	790.00	766.00	777.00
Debt-to-Income	Mean	37.19	37.23	38.24	40.38	39.56
	Sd	10.10	10.31	11.59	11.08	10.78
	q5	19.00	19.00	18.00	21.00	21.00
	Median	39.00	39.00	39.00	41.00	40.00
	q95	51.00	52.00	58.00	59.00	58.00
Loan-to-Value	Mean	76.08	75.24	80.57	81.52	77.95
	Sd	17.06	17.67	14.08	12.26	15.26
	q5	44.00	42.00	56.00	60.00	51.00
	Median	80.00	79.00	80.00	80.00	80.00
	q95	97.00	97.00	100.00	100.00	98.00
Interest Rate	Mean	5.04	5.15	6.11	6.35	5.74
	Sd	1.21	1.30	1.03	0.80	0.99
	q5	3.38	3.25	4.25	5.13	3.88
	Median	4.88	5.00	6.25	6.38	5.88
	q95	7.13	7.38	7.63	7.63	7.13
Balance	Mean	199,217	195,622	167,889	182,730	199,602
	Sd	122,780	124,086	98,844	95,368	103,121
	q5	56,000	53,000	50,000	59,000	66,000
	Median	169,000	164,000	145,000	164,000	180,000
	q95	421,000	423,000	362,000	370,000	397,000
Loan Age	Mean	67.92	67.06	59.28	51.33	70.96
	Sd	43.71	49.12	36.93	29.62	39.56
	q5	15.00	12.00	8.00	16.00	21.00
	Median	58.00	54.00	54.00	44.00	63.00
	q95	151.00	168.00	128.00	110.00	148.00
Remaining Term	Mean	255.95	259.43	282.95	401.54	414.61
	Sd	84.25	89.84	64.23	87.91	97.38
	q5	82.00	73.00	136.00	264.00	214.00
	Median	287.00	293.00	300.00	460.00	478.00
	q95	343.00	348.00	350.00	479.00	480.00
Time Since Default	Mean	13.41	10.56	15.10	14.03	17.81
	Sd	10.59	13.61	16.77	14.52	19.97
	q5	6.00	0.00	0.00	3.00	3.00
	Median	10.00	6.00	10.00	9.00	11.00
	q95	31.00	32.00	48.00	43.00	59.00

Table 5.5: Determinants of Mortgage Post-Default Outcomes by Policy Periods: Marginal Effects

The Table shows average marginal effects of explanatory variables on the different outcomes of multinomial logistic regression with policy period interaction terms. The baseline outcome is *Delinquency*, and it is not displayed being the reference category. The outcomes reported are: $Cure$, $Modification$ and *Liquidation*. Standard errors of marginal effects are calculated using the delta method and are reported in parentheses. *Credit Score* is borrower's Credit Score at origination. *Debt-to-Income* is the sum of borrower's monthly debt payments, including housing expenses that incorporate mortgage payment, divided by total monthly income used for underwriting. *Joint* captures loans with more than one borrower. *Loan-to-Value* is the ratio between $Balance_t$ and $PropertyPrice_t$ at origination. *Judicial* differentiate Judicial from Non-judicial states; *Non Recourse* differentiate Recourse States from Non-recourse states; *Not Single-family* distinguished Single-Family from other property types. TPO catches mortgages originated by Third Parties; *Non-Cashout Refi* and *Purchase* separate loan purpose categories from *Non-Cashout Refinance*, which is the reference category. *Primary* and *Second Home* separate occupancy type categories from *Investment*, which is the reference category. *Mortgage Insurance* captures the mortgages having an insurance against default. *Loan Age* is mortgage age since origination, reported in months. *Time since Default* is the number of months from default to time t. *Balance* is the current outstanding balance at time t in logarithmic scale. *IR Spread* is the difference between mortgage interest rate at origination and Freddie Mac 30-Year interest rate curve. Ump_{12}^{lag2Yr} is the 1-year growth rate of State-level Unemployment, lagged by 2 years. *Region* FE are regional fixed effects in which regions are obtained from the US state groupings produced by the US Bureau of Economic Analysis (BEA); *Default Period* FE are fixed effects capturing the policy period when the loan defaulted in first instance. The $Crisis$ period spans over the years during the HAMP program (from 2009 to 2016) and is activated using a dummy variable for the observations in this period. The $PostCrisis$ period spans over the years following the lift of HAMP (from 2016) and is activated using a dummy variable for the observations in this period. The sample includes mortgages originated from 1999 to 2022 and observed during the same time span. ***, **, * denote statistical significance at the 1%, 5% and 10% levels respectively.

Variable	Cure	Modification	Liquidation
Credit Score	0.0000401***	-0.0000393***	0.0000763***
	(0.00000158)	(0.0000011)	(0.00000155)
Debt-to-Income	-0.0001398***	0.0000572***	0.0000107*
	(0.00000665)	(0.00000522)	(0.0000061)
Loan-to-Value	-0.0003226***	0.0000955***	0.0004268***
	(0.00000806)	(0.00000772)	(0.0000109)
Joint	0.0045166***	0.0010225***	-0.0005152***
	(0.0001724)	(0.0001231)	(0.0001526)
Judicial	-0.0014088***	-0.0008541***	-0.0080484***
	(0.0001703)	(0.000128)	(0.0001604)
Non Recourse	0.0015608***	-0.000502***	-0.0027441***
	(0.0002164)	(0.0001555)	(0.0001811)
Not Single-Family	-0.0002044	-0.0000675	0.0039062***
	(0.0002342)	(0.000177)	(0.0002322)
TPO	-0.0008074***	0.0009229***	-0.0004309***
	(0.0001608)	(0.0001264)	(0.0001525)
Non-Cashout Refi	0.0018156***	-0.0006261***	0.0016574***
	(0.000179)	(0.0001505)	(0.0001896)
Purchase	0.0049479***	-0.0003177***	-0.003308***
	(0.0002307)	(0.0001676)	(0.0001955)
Primary	0.0015631***	0.0051022***	-0.0153663***
	(0.0003582)	(0.0002678)	(0.000416)
Second Home	0.0056623***	-0.0005146	0.0005748
	(0.0006654)	(0.0004111)	(0.0008263)

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Table 5.5

Variable	Cure	Modification	Liquidation
Mortgage Insurance	-0.0002697*	0.0009129***	-0.0013129***
	(0.0002222)	(0.0001866)	(0.0002213)
Loan Age	-0.0000158***	0.0000331***	-0.0002785***
	(0.00000435)	(0.00000348)	(0.00000397)
Time since Default	0.0002305***	-0.0000606***	-0.0000725***
	(0.00000709)	(0.00000556)	(0.00000773)
Balance	-0.0023551***	0.0049082***	-0.003504***
	(0.0001409)	(0.0001435)	(0.0001361)
Crisis*Credit Score	-0.00000623***	-0.0000324***	0.0001178***
	(0.000000373)	(-0.0000324)	(0.000000736)
Crisis*Debt-to-Income	-0.0000142***	0.0001266***	-0.0000041
	(0.00000162)	(0.00000256)	(0.00000294)
Crisis*Loan-to-Value	-0.0000932***	0.0000305***	0.0003481***
	(0.00000175)	(0.00000273)	(0.00000347)
Crisis*Joint	0.0010594***	0.0006333***	0.0006228***
	(0.0000434)	(0.0000647)	(0.0000773)
Crisis*Judicial	-0.0024807***	-0.0031804***	-0.0090644***
	(0.0000497)	(0.0000803)	(0.0000955)
Crisis*Non Recourse	-0.0001597***	0.0014908***	0.0031917***
	(0.0000595)	(0.0001006)	(0.0001154)
Crisis*Not Single-Family	-0.0010202***	-0.0014926***	0.0056686***
	(0.0000517)	(0.0000787)	(0.0000978)
Crisis*TPO	-0.0014237***	0.0000806	-0.00011
	(0.0000413)	(0.0000648)	(0.0000747)
Crisis*Non-Cashout Refi	0.0011184***	-0.0016051***	0.0004862***
	(0.0000485)	(0.00008)	(0.000094)
Crisis*Purchase	0.0012917***	-0.0025511*	0.0007937***
	(0.0000577)	(0.0000846)	(0.0000971)
Crisis*Primary	0.0008967***	0.0093537***	-0.0085265***
	(0.0000866)	(0.0001067)	(0.0001771)
Crisis*Second Home	0.0012283***	0.0010785***	-0.0010969***
	(0.0001492)	(0.0001688)	(0.0002761)
Crisis*Mortgage Insurance	-0.0001362**	0.0012561***	-0.0025167***
	(0.0000626)	(0.0000939)	(0.0000986)
Crisis*Loan Age	0.0000568***	0.0000333***	-0.0001347***
	(0.000000731)	(0.00000117)	(0.00000146)
Crisis*Time since Default	-0.0000203***	0.00000184	0.0000763***
	(0.00000119)	(0.00000203)	(0.00000266)
Crisis*Balance	-0.0023831***	0.0075327***	-0.0022321***
	(0.0000419)	(0.0000669)	(0.0000762)
PostCrisis*Credit Score	0.0000029**	-0.0000398***	0.0001243***
	(0.00000121)	(0.00000162)	(0.00000296)
PostCrisis*Debt-to-Income	-0.0000605***	0.0000406***	0.0000317***
	(0.00000549)	(0.00000741)	(0.0000116)
PostCrisis*Loan-to-Value	-0.0000793***	0.000044***	0.0003323***
	(0.00000462)	(5.8)	(0.00000961)
PostCrisis*Joint	0.0013754***	0.0027167***	-0.0002639
	(0.0001484)	(0.0001923)	(0.0003136)
PostCrisis*Judicial	-0.0016387***	0.0022635***	-0.0022514***
	(0.0001536)	(0.0001974)	(0.0003006)
PostCrisis*Non Recourse	0.0015923***	-0.0017115***	-0.0000445
	(0.0001989)	(0.0002525)	(0.0003886)
PostCrisis*Not Single-Family	0.0006469***	0.0033326***	-0.0016024***
	(0.0001674)	(0.0002231)	(0.0003398)

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Table 5.5

Variable	Cure	Modification	Liquidation
PostCrisis*TPO	-0.000698***	-0.0024455***	0.0043984***
	(0.0002162)	(0.0002976)	(0.0004973)
PostCrisis*Non-Cashout Refi	0.0008719***	-0.0013844***	-0.0014935***
	(0.0001771)	(0.0002588)	(0.0004325)
PostCrisis*Purchase	0.0027417***	-0.0010393***	-0.0051637***
	(0.0002024)	(0.0002669)	(0.0004298)
PostCrisis*Primary	-0.0025382***	0.0044764***	-0.0130164***
	(0.0003226)	(0.0003652)	(0.0006895)
PostCrisis*Second Home	-0.0011912**	0.0004057	-0.0029121**
	(0.0005347)	(0.0006257)	(0.0012266)
PostCrisis*Mortgage Insurance	-0.0019696***	0.0010854***	0.0028731***
	(0.0001885)	(0.0002483)	(0.0003835)
PostCrisis*Loan Age	0.0000353***	-0.0000306***	-0.0001787***
	(0.00000159)	(0.00000248)	(0.00000561)
PostCrisis*Time since Default	-0.0000494***	0.0000947***	0.0000249***
	(0.00000384)	(0.0000042)	(0.00000652)
PostCrisis*Balance	-0.0000604	0.0054786***	-0.0075988***
	(0.0001187)	(0.0001664)	(0.0002793)
IR Spread	-0.0016823***	-0.0009238***	0.0038128***
	(0.0000262)	(0.0000358)	(0.0000439)
Ump_{12}^{lag2Yr}	0.0000454***	-0.0003245***	0.0001854***
	(0.0000152)	(0.0000189)	(0.0000216)
During-HAMP	0.0034093***	0.0026621***	0.0000434
	(0.0000944)	(0.0001016)	(0.0001411)
Post-HAMP	0.0029272***	0.0063236***	-0.0079721***
	(0.0001745)	(0.0002766)	(0.0002664)
Region FE	Yes		
Log-Likelihood	-5812181.8		
Pseudo R2	0.0279		
N.Observations	23,293,151		
N.Mortgages	1,453,556		

Table 5.6: Determinants of Mortgage Post-Default Outcomes by Policy Periods: Relative Risk Ratios

The Table shows *Relative Risk Ratios* of explanatory variables on the different outcomes of multinomial logistic regression with policy period interaction terms. The baseline outcome is *Delinquency*, and it is not displayed being the reference category. The outcomes reported are: $Cure$, $Modification$ and *Liquidation*. Standard errors of marginal effects are calculated using the delta method and are reported in parentheses. *Credit Score* is borrower's Credit Score at origination. *Debt-to-Income* is the sum of borrower's monthly debt payments, including housing expenses that incorporate mortgage payment, divided by total monthly income used for underwriting. *Joint* captures loans with more than one borrower. *Loan-to-Value* is the ratio between $Balance_t$ and $PropertyPrice_t$ at origination. *Judicial* differentiate Judicial from Non-judicial states; *Non Recourse* differentiate Recourse States from Non-recourse states; *Not Single-family* distinguished Single-Family from other property types. TPO catches mortgages originated by Third Parties; *Non-Cashout Refi* and *Purchase* separate loan purpose categories from *Non-Cashout Refinance*, which is the reference category. *Primary* and *Second Home* separate occupancy type categories from *Investment*, which is the reference category. *Mortgage Insurance* captures the mortgages having an insurance against default. *Loan Age* is mortgage age since origination, reported in months. *Time since Default* is the number of months from default to time t. *Balance* is the current outstanding balance at time t in logarithmic scale. *IR Spread* is the difference between mortgage interest rate at origination and Freddie Mac 30-Year interest rate curve. Ump_{12}^{lag2Yr} is the 1-year growth rate of State-level Unemployment, lagged by 2 years. *Region* FE are regional fixed effects in which regions are obtained from the US state groupings produced by the US Bureau of Economic Analysis (BEA); *Default Period* FE are fixed effects capturing the policy period when the loan defaulted in first instance. The *Crisis* period spans over the years during the HAMP program (from 2009 to 2016) and is activated using a dummy variable for the observations in this period. The *PostCrisis* period spans over the years following the lift of HAMP (from 2016) and is activated using a dummy variable for the observations in this period. The sample includes mortgages originated from 1999 to 2022 and observed during the same time span. ***, **, * denote statistical significance at the 1%, 5% and 10% levels respectively.

Variable	Cure	Modification	Liquidation
Credit Score	1.00239***	0.9966177***	1.00353***
	(0.0000854)	(0.0000941)	(0.0000642)
Debt-to-Income	0.9918878***	1.004994***	1.000417
	(0.0003808)	(0.0004573)	(0.0002812)
Loan-to-Value	0.9817262***	1.008682***	1.019704***
	(0.0003843)	(0.0006856)	(0.0004838)
Joint	1.29783***	1.099378***	0.9816987***
	(0.0122639)	(0.012052)	(0.0069435)
Judicial	0.9128264***	0.9178163***	0.6863758***
	(0.009135)	(0.0104958)	(0.00489)
Non Recourse	1.090259***	0.9544261***	0.8782018***
	(0.0131526)	(0.0135804)	(0.0078107)
Not Single-Family	0.9916572	0.9977312	1.187842***
	(0.0137373)	(0.0158187)	(0.0114525)
TPO	0.9540793***	1.084501***	0.9804423***
	(0.008979)	(0.0122982)	(0.0068973)
Non-Cashout Refi	1.120562***	0.9488457***	1.075837***
	(0.0124104)	(0.0127062)	(0.0088869)
Purchase	1.322467***	0.9737616*	0.8558239***
	(0.0164989)	(0.0143792)	(0.0079665)
Primary	1.090471***	1.753834***	0.566505***
	(0.0250802)	(0.0693301)	(0.0067642)
Second Home	1.368308***	0.927583	1.021763
	(0.0480963)	(0.0608708)	(0.0243351)

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Table 5.6

Variable	Cure	Modification	Liquidation
Mortgage Insurance	0.9838616	1.081834***	0.9412425***
	(0.0129463)	(0.0175168)	(0.0097395)
Loan Age	0.9988384***	1.002658***	0.9872306***
	(0.0002605)	(0.0002908)	(0.0002009)
Time since Default	1.013496***	0.99475***	0.9968127***
	(0.0003959)	(0.0004859)	(0.0003573)
Balance	0.8720642***	1.540864***	0.852834***
	(0.0074483)	(0.0158077)	(0.0055884)
Crisis*Credit Score	0.9968355***	1.001607***	1.001375***
	(0.0000982)	(0.0000998)	(0.0000693)
Crisis*Debt-to-Income	1.006318***	1.002421***	0.9995265
	(0.0004445)	(0.0004785)	(0.000303)
Crisis*Loan-to-Value	1.005905***	0.9934212***	0.9950275***
	(0.0004539)	(0.000692)	(0.0004909)
Crisis*Joint	0.892301***	0.9455685***	1.04727***
	(0.009857)	(0.0109272)	(0.0080124)
Crisis*Judicial	0.7657319***	0.8932887***	0.9872664*
	(0.0086733)	(0.0106111)	(0.0073842)
Crisis*Non Recourse	0.9012041***	1.144791***	1.298199***
	(0.0123123)	(0.016833)	(0.0121186)
Crisis*Not Single-Family	0.8729627***	0.9205572***	1.050364***
	(0.0137595)	(0.0152035)	(0.0106635)
Crisis*TPO	0.8589039***	0.9249694***	1.013928*
	(0.0093891)	(0.0110146)	(0.0076816)
Crisis*Non-Cashout Refi	1.044627***	0.9632682***	0.9482493***
	(0.0134598)	(0.0135764)	(0.0085436)
Crisis*Purchase	0.9046749*	0.8861551***	1.206379***
	(0.0132433)	(0.0137704)	(0.0120893)
Crisis*Primary	1.047653***	1.185364***	1.29937***
	(0.0276652)	(0.048846)	(0.0169566)
Crisis*Second Home	0.8719986***	1.213098***	0.946359**
	(0.0353557)	(0.0825502)	(0.0237721)
Crisis*Mortgage Insurance	0.9961533	0.9910968	0.9553831***
	(0.0156393)	(0.0168406)	(0.0105574)
Crisis*Loan Age	1.008988***	0.999219***	1.007322***
	(0.0002795)	(0.0002968)	(0.0002122)
Crisis*Time since Default	0.9839878***	1.005443***	1.006391***
	(0.0004046)	(0.0005035)	(0.0003648)
Crisis*Balance	0.8286298***	1.004289	1.073601***
	(0.0082577)	(0.010868)	(0.0076289)
PostCrisis*Credit Score	0.997915***	1.001705***	1.001095***
	(0.0001227)	(0.0001179)	(0.0001158)
PostCrisis*Debt-to-Income	1.003749***	0.9968392***	1.000749
	(0.000552)	(0.0005649)	(0.0005175)
PostCrisis*Loan-to-Value	1.013039***	0.9936359***	0.9929294***
	(0.0005179)	(0.0007236)	(0.0005754)
PostCrisis*Joint	0.8548032***	1.029749**	1.012844
	(0.0121361)	(0.0142458)	(0.0138942)
PostCrisis*Judicial	0.9699959**	1.203246***	1.339944***
	(0.0138885)	(0.016947)	(0.0172663)
PostCrisis*Non Recourse	1.026597	0.9690413*	1.136667***
	(0.0180159)	(0.017632)	(0.0190678)
PostCrisis*Not Single-Family	1.059234***	1.158381***	0.7951959***
	(0.019324)	(0.0212318)	(0.0129139)

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Table 5.6

Variable	Cure	Modification	Liquidation
PostCrisis*TPO	0.9971592	0.8277081***	1.198895***
	(0.0186665)	(0.0149177)	(0.0225265)
PostCrisis*Non-Cashout Refi	0.9519686***	0.9890737	0.8809124***
	(0.0166837)	(0.0175588)	(0.01533)
PostCrisis*Purchase	0.9169582***	0.9776263	0.9619951**
	(0.0174385)	(0.0185731)	(0.0177835)
PostCrisis*Primary	0.7634776***	0.7012819***	1.165289***
	(0.023457)	(0.0309846)	(0.0255583)
PostCrisis*Second Home	0.6740254***	1.097649	0.9022495**
	(0.0336078)	(0.0811685)	(0.0377642)
PostCrisis*Mortgage Insurance	0.8770343***	0.9715085	1.179848***
	(0.0173997)	(0.0190363)	(0.0203241)
PostCrisis*Loan Age	1.003564***	0.9958144***	1.006179***
	(0.0002906)	(0.0003073)	(0.0002572)
PostCrisis*Time since Default	0.9832066***	1.009598***	1.004178***
	(0.0004597)	(0.0005357)	(0.0004372)
PostCrisis*Balance	1.13934***	0.8265511***	0.8868922***
	(0.0137828)	(0.01031)	(0.0104257)
IR Spread	0.8329588***	0.9489057***	1.166036***
	(0.002385)	(0.0020017)	(0.002088)
Ump_{12}^{lag2Yr}	1.004865***	0.9812566***	1.007338***
	(0.0016785)	(0.0010939)	(0.000889)
During-HAMP	1.489276***	1.186388**	1.007866
	(0.0169848)	(0.0079619)	(0.0057424)
Post-HAMP	1.41401***	1.427617***	0.6880714***
	(0.0271227)	(0.0204716)	(0.6880714)
Region FE	Yes		
Log-Likelihood	-5812181.8		
Pseudo R2	0.0279		
N.Observations	23,293,151		
N.Mortgages	1,453,556		

Table 5.7: Determinants of Mortgage Post-Default Outcomes by Policy Periods and Additional Modification Outcomes: Marginal Effects

The Table shows average marginal effects of explanatory variables on the different outcomes of multinomial logistic regression with policy period interaction terms. The baseline outcome is *Delinquency*, and it is not displayed being the reference category. The outcomes reported are: *Cure*, *Successful* and *Failed Modification* and *Liquidation*. Standard errors of marginal effects are calculated using the delta method and are reported in parentheses. *Credit Score* is borrower's Credit Score at origination. *Debt-to-Income* is the sum of borrower's monthly debt payments, including housing expenses that incorporate mortgage payment, divided by total monthly income used for underwriting. *Joint* captures loans with more than one borrower. *Loan-to-Value* is the ratio between $Balance_t$ and $PropertyPrice_t$ at origination. *Judicial* differentiate Judicial from Non-judicial states; *Non Recourse* differentiate Recourse States from Non-recourse states; *Not Single-family* distinguished Single-Family from other property types. *TPO* catches mortgages originated by Third Parties; *Non-Cashout Refi* and *Purchase* separate loan purpose categories from *Non-Cashout Refinance*, which is the reference category. *Primary* and *Second Home* separate occupancy type categories from *Investment*, which is the reference category. *Mortgage Insurance* captures the mortgages having an insurance against default. *Loan Age* is mortgage age since origination, reported in months. *Time since Default* is the number of months from default to time t. *Balance* is the current outstanding balance at time t in logarithmic scale. *IR Spread* is the difference between mortgage interest rate at origination and Freddie Mac 30-Year interest rate curve. Ump_{12}^{lag2Yr} is the 1-year growth rate of State-level Unemployment, lagged by 2 years. *Region* FE are regional fixed effects in which regions are obtained from the US state groupings produced by the US Bureau of Economic Analysis (BEA); *Default Period* FE are fixed effects capturing the policy period when the loan defaulted in first instance. The *Crisis* period spans over the years during the HAMP program (from 2009 to 2016) and is activated using a dummy variable for the observations in this period. The *PostCrisis* period spans over the years following the lift of HAMP (from 2016) and is activated using a dummy variable for the observations in this period. The sample includes mortgages originated from 1999 to 2022 and observed during the same time span. ***, **, * denote statistical significance at the 1%, 5% and 10% levels respectively.

Variable	Cure	Mod. Success	Mod. Failed	Liquidation
Credit Score	0.00004***	-0.0000273***	-0.00000991***	0.0000762***
	(0.00000158)	(0.00000112)	(0.000000382)	(0.00000155)
Debt-to-Income	-0.0001397***	0.0000288***	0.0000201***	0.0000109***
	(0.00000665)	(0.00000531)	(0.00000192)	(0.0000061)
Loan-to-Value	-0.0003219***	-0.00000269	0.000062***	0.0004275***
	(0.00000805)	(0.000007)	(0.00000355)	(0.0000109)
Joint	0.0045011***	0.0022356***	-0.0003484***	-0.0005301***
	(0.0001723)	(0.0001289)	(0.0000448)	(0.0001526)
Judicial	-0.0014104***	-0.0001931	-0.0005243***	-0.0080498***
	(0.0001703)	(0.0001315)	(0.0000473)	(0.0001604)
Non Recourse	0.0015637***	-0.0006955***	0.0000614	-0.0027437***
	(0.0002165)	(0.0001591)	(0.000058)	(0.0001811)
Not Single-Family	-0.0002017	-0.0004719***	0.0002541***	0.0039079***
	(0.0002342)	(0.0001823)	(0.0000661)	(0.0002322)
TPO	-0.0008057***	0.0005391***	0.0002427***	-0.0004276***
	(0.0001608)	(0.00013)	(0.0000458)	(0.0001525)
Non-Cashout Refi	0.0018102***	0.0001895	-0.0004838***	0.0016501***
	(0.000179)	(0.000152)	(0.0000569)	(0.0001896)
Purchase	0.0049456***	0.0001319	-0.0003127***	-0.0033108***
	(0.0002307)	(0.000171)	(0.0000627)	(0.0001955)
Primary	0.0015504***	0.0049016***	0.0008337***	-0.0153766***
	(0.0003584)	(0.0002602)	(0.0001044)	(0.0004161)
Second Home	0.0056605***	-0.0000943	-0.0001884	0.000567
	(0.0006658)	(0.0004014)	(0.0001619)	(0.0008264)

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Table 5.7

Variable	Cure	Mod. Success	Mod. Failed	Liquidation
Mortgage Insurance	-0.0002701	0.0009807***	-0.0000846	-0.001311***
	(0.0002221)	(0.0001915)	(0.000069)	(0.0002213)
Loan Age	-0.0000162***	0.0000638***	-0.00000888***	-0.0002789***
	(0.00000434)	(0.00000394)	(0.00000118)	(0.00000397)
Time since Default	0.0002307***	-0.0000737***	-0.00000274	-0.0000723***
	(0.00000709)	(0.00000583)	(0.00000195)	(0.00000773)
Balance	-0.0023633***	0.0040893***	0.0012165***	-0.0035066***
	(0.0001409)	(0.0001504)	(0.0000526)	(0.0001361)
Crisis*Credit Score	-0.00000622***	-0.000024***	-0.00000927***	0.0001178***
	(0.000000372)	(0.000000525)	(0.000000281)	(0.000000735)
Crisis*Debt-to-Income	-0.0000142***	0.0001157***	0.0000101***	-0.00000407
	(0.00000162)	(0.00000231)	(0.00000124)	(0.00000294)
Crisis*Loan-to-Value	-0.0000932***	0.00000732***	0.0000361***	0.0003477***
	(0.00000175)	(0.00000246)	(0.00000128)	(0.00000347)
Crisis*Joint	0.001059***	0.0007158***	-0.0000781**	0.0006226***
	(0.0000434)	(0.0000584)	(0.0000317)	(0.0000772)
Crisis*Judicial	-0.0024796***	-0.0023051***	-0.001***	-0.0090593***
	(0.0000497)	(0.0000729)	(0.0000389)	(0.0000955)
Crisis*Non Recourse	-0.0001599***	0.0010713***	0.0004828***	0.0031886***
	(0.0000595)	(0.0000909)	(0.0000489)	(0.0001154)
Crisis*Not Single-Family	-0.0010199***	-0.0013755***	-0.0001003***	0.0056666***
	(0.0000517)	(0.0000709)	(0.0000388)	(0.0000978)
Crisis*TPO	-0.0014235***	-0.0004822***	0.0006345***	-0.0001123
	(0.0000413)	(0.0000583)	(0.0000324)	(0.0000747)
Crisis*Non-Cashout Refi	0.0011189***	-0.00096***	-0.0007993***	0.0004904***
	(0.0000484)	(0.0000718)	(0.0000414)	(0.000094)
Crisis*Purchase	0.0012924***	-0.0022759***	-0.000428***	0.0007969***
	(0.0000577)	(0.0000757)	(0.0000429)	(0.0000971)
Crisis*Primary	0.0008948***	0.007847***	0.0017079***	-0.0085296***
	(0.0000866)	(0.0000955)	(0.0000527)	(0.0001771)
Crisis*Second Home	0.0012276***	0.001024***	0.0001222	-0.0010979***
	(0.0001492)	(0.0001523)	(0.0000822)	(0.0002761)
Crisis*Mortgage Insurance	-0.0001345**	-0.0000028	0.0010969***	-0.0025144***
	(0.0000626)	(0.0000835)	(0.0000452)	(0.0000986)
Crisis*Loan Age	0.0000569***	0.000063***	-0.0000424***	-0.0001344***
	(0.00000073)	(0.00000104)	(0.000000721)	(0.00000146)
Crisis*Time since Default	-0.0000203***	0.0000177***	-0.000014***	0.0000762***
	(0.00000119)	(0.00000178)	(0.00000118)	(0.00000266)
Crisis*Balance	-0.0023825***	0.0067283***	0.0007374***	-0.0022298***
	(0.0000419)	(0.0000608)	(0.0000309)	(0.0000762)
PostCrisis*Credit Score	0.0000029**	-0.0000361***	-0.00000343***	0.0001244***
	(0.00000121)	(0.00000146)	(0.000000864)	(0.00000296)
PostCrisis*Debt-to-Income	-0.0000604***	0.0000365***	-0.00000709*	0.000032
	(0.00000549)	(0.00000665)	(0.0000042)	(0.0000116)
PostCrisis*Loan-to-Value	-0.0000796***	0.0000357***	0.0000305***	0.000332***
	(0.00000463)	(0.00000519)	(0.00000336)	(0.00000962)
PostCrisis*Joint	0.0013815***	0.0025014***	-0.0002053**	-0.0002524
	(0.0001484)	(0.0001728)	(0.0001002)	(0.0003139)
PostCrisis*Judicial	-0.0016381***	0.0023971***	-0.0002488**	-0.0022549***
	(0.0001537)	(0.0001796)	(0.0001021)	(0.0003008)
PostCrisis*Non Recourse	0.0015923***	-0.0015555***	-0.0000983	-0.0000455
	(0.000199)	(0.0002286)	(0.0001309)	(0.0003888)
PostCrisis*Not Single-Family	0.0006541***	0.0030311***	-0.000231**	-0.0015873***
	(0.0001675)	(0.0002008)	(0.0001084)	(0.0003402)

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Table 5.7

Variable	Cure	Mod. Success	Mod. Failed	Liquidation
PostCrisis*TPO	-0.0007024***	-0.0019643***	-0.0001564	0.0043946***
	(0.0002163)	(0.0002684)	(0.0001597)	(0.0004976)
PostCrisis*Non-Cashout Refi	0.0008739***	-0.0011586***	-0.0003356***	-0.0014898**
	(0.0001772)	(0.0002322)	(0.0001461)	(0.0004329)
PostCrisis*Purchase	0.002741***	-0.0008991***	0.0000143	-0.0051717***
	(0.0002024)	(0.0002393)	(0.0001554)	(0.0004301)
PostCrisis*Primary	-0.0025298***	0.0040699***	-0.0002441	-0.0130029***
	(0.0003225)	(0.0003278)	(0.000212)	(0.0006897)
PostCrisis*Second Home	-0.0011873**	0.0003049	-0.0001819	-0.0029012**
	(0.0005347)	(0.0005584)	(0.0003765)	(0.0012272)
PostCrisis*Mortgage Insurance	-0.0019714***	0.0009547***	0.0002211*	0.0028712***
	(0.0001886)	(0.0002233)	(0.0001244)	(0.0003838)
PostCrisis*Loan Age	0.0000353***	-0.0000203***	-0.0000118***	-0.0001788***
	(0.00000159)	(0.00000221)	(0.00000176)	(0.00000561)
PostCrisis*Time since Default	-0.0000493***	0.0001031***	-0.0000102***	0.000025***
	(0.00000384)	(0.0000038)	(0.00000253)	(0.00000652)
PostCrisis*Balance	-0.0000519	0.0047075***	0.0000426	-0.0075841***
	(0.0001188)	(0.0001499)	(0.0000846)	(0.0002794)
IR Spread	-0.0016818***	-0.0011051***	0.0001506***	0.0038135***
	(0.0000262)	(0.0000332)	(0.000014)	(0.0000439)
Ump_{12}^{lag2Yr}	0.000045***	-0.000315***	0.000069***	0.000183***
	(0.0000152)	(-0.000315***)	(0.0000076)	(0.0000216)
During-HAMP	0.0034102***	0.004817***	-0.0019982***	0.0000395
	(0.0000944)	(0.0000823)	(0.0000523)	(0.0001412)
Post-HAMP	0.0029385***	0.0088209***	-0.0035047***	-0.0079543***
	(0.0001748)	(0.0002476)	(0.0000847)	(0.0002668)
Region FE	Yes			
Log-Likelihood	-5970679.5			
Pseudo R2	0.0312			
N.Observations	23,293,151			
N.Mortgages	1,453,556			

Table 5.8: Determinants of Mortgage Post-Default Outcomes by Policy Periods and Additional Modification Outcomes: Marginal Effects

The Table shows *Relative Risk Ratios* of explanatory variables on the different outcomes of multinomial logistic regression with policy period interaction terms. The baseline outcome is *Delinquency*, and it is not displayed being the reference category. The outcomes reported are: *Cure*, $Successful$ and *Failed Modification* and *Liquidation.* Standard errors of marginal effects are calculated using the delta method and are reported in parentheses. *Credit Score* is borrower's Credit Score at origination. *Debt-to-Income* is the sum of borrower's monthly debt payments, including housing expenses that incorporate mortgage payment, divided by total monthly income used for underwriting. *Joint* captures loans with more than one borrower. *Loan-to-Value* is the ratio between $Balance_t$ and $PropertyPrice_t$ at origination. *Judicial* differentiate Judicial from Non-judicial states; *Non Recourse* differentiate Recourse States from Non-recourse states; *Not Single-family* distinguished Single-Family from other property types. TPO catches mortgages originated by Third Parties; *Non-Cashout Refi* and *Purchase* separate loan purpose categories from *Non-Cashout Refinance*, which is the reference category. *Primary* and *Second Home* separate occupancy type categories from *Investment*, which is the reference category. *Mortgage Insurance* captures the mortgages having an insurance against default. *Loan Age* is mortgage age since origination, reported in months. *Time since Default* is the number of months from default to time t. *Balance* is the current outstanding balance at time t in logarithmic scale. *IR Spread* is the difference between mortgage interest rate at origination and Freddie Mac 30-Year interest rate curve. Ump_{12}^{lag2Yr} is the 1-year growth rate of State-level Unemployment, lagged by 2 years. *Region* FE are regional fixed effects in which regions are obtained from the US state groupings produced by the US Bureau of Economic Analysis (BEA); *Default Period* FE are fixed effects capturing the policy period when the loan defaulted in first instance. The $Crisis$ period spans over the years during the HAMP program (from 2009 to 2016) and is activated using a dummy variable for the observations in this period. The *PostCrisis* period spans over the years following the lift of HAMP (from 2016) and is activated using a dummy variable for the observations in this period. The sample includes mortgages originated from 1999 to 2022 and observed during the same time span. ***, **, * denote statistical significance at the 1%, 5% and 10% levels respectively.

Variable	Cure	Mod. Success	Mod. Failed	Liquidation
Credit Score	1.00239***	0.9970369***	0.9962761***	1.003529***
	(0.0000854)	(0.0001206)	(0.0001425)	(0.0000642)
Debt-to-Income	0.9918859***	1.003118***	1.007733***	1.00042
	(0.0003808)	(0.0005888)	(0.0007181)	(0.0002812)
Loan-to-Value	0.9817205***	0.99982	1.024485***	1.019712***
	(0.0003843)	(0.0007872)	(0.0013058)	(0.0004839)
Joint	1.297935***	1.287823***	0.8779663***	0.9815737***
	(0.0122646)	(0.0183157)	(0.8779663)	(0.0069425)
Judicial	0.9128919***	0.9695517**	0.8075922***	0.686359***
	(0.0091361)	(0.0143154)	(0.0146097)	(0.00489)
Non Recourse	1.09025***	0.9225886***	1.02106	0.878181***
	(0.0131533)	(0.0171863)	(0.0225536)	(0.0078109)
Not Single-Family	0.9916181	0.9510425**	1.104587***	1.18787***
	(0.0137366)	(0.0201262)	(0.0264967)	(0.0114527)
TPO	0.954053***	1.061283***	1.09794***	0.9804456***
	(0.0089787)	(0.0155178)	(0.0197208)	(0.0068972)
Non-Cashout Refi	1.120628***	1.024433	0.8338739***	1.075718***
	(0.0124113)	(0.0175029)	(0.0178109)	(0.0088861)
Purchase	1.322533***	1.016785	0.8908114***	0.8557637***
	(0.0164998)	(0.0195943)	(0.0204404)	(0.007966)
Primary	1.090476***	2.084963***	1.438738***	0.5665032***
	(0.0250803)	(0.1163786)	(0.0813436)	(0.0067641)
Second Home	1.368268***	0.9849109	0.9018154	1.021748
	(0.0480948)	(0.0901555)	(0.0856368)	(0.0243351)

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Table 5.8

Variable	Cure	Mod. Success	Mod. Failed	Liquidation
Mortgage Insurance	0.9838892	1.111593***	0.9669162	0.9411878***
	(0.0129467)	(0.0227422)	(0.0258984)	(0.0097394)
Loan Age	0.9988418***	1.006903***	0.9962891***	0.9872273***
	(0.0002605)	(0.0003629)	(0.0004766)	(0.0002009)
Time since Default	1.013494***	0.9919263***	0.9989745	0.9968146***
	(0.0003959)	(0.0006223)	(0.0007541)	(0.0003574)
Balance	0.8720721***	1.575446***	1.596632***	0.8529058***
	(0.0074484)	(0.0206211)	(0.0263722)	(0.0055887)
Crisis*Credit Score	0.9968354***	1.001351***	1.001157***	1.001376***
	(0.0000982)	(0.0001263)	(0.000162)	(0.0000693)
Crisis*Debt-to-Income	1.006323***	1.005161***	0.99534***	0.9995222
	(0.0004445)	(0.0006118)	(0.0007927)	(0.000303)
Crisis*Loan-to-Value	1.005908***	1.000983	0.9866713***	0.9950237***
	(0.0004539)	(0.0008065)	(0.0013052)	(0.000491)
Crisis*Joint	0.8922678***	0.8185799***	1.116052***	1.047373***
	(0.0098564)	(0.0121126)	(0.0218013)	(0.008013)
Crisis*Judicial	0.765699***	0.8634001***	0.9126578***	0.9872154*
	(0.0086732)	(0.0131323)	(0.0180336)	(0.0073838)
Crisis*Non Recourse	0.9012024***	1.17257***	1.125739***	1.298243***
	(0.0123125)	(0.0223953)	(0.0270013)	(0.0121192)
Crisis*Not Single-Family	0.8729639***	0.9543565**	0.8829924***	1.050362***
	(0.0137594)	(0.0207851)	(0.0233283)	(0.0106633)
Crisis*TPO	0.8588345***	0.9093498***	1.09439***	1.013995*
	(0.0093883)	(0.013796)	(0.0221128)	(0.0076819)
Crisis*Non-Cashout Refi	1.044644***	0.9142743***	0.9516878**	0.9483086***
	(0.0134602)	(0.0162392)	(0.0232418)	(0.0085441)
Crisis*Purchase	0.9046022***	0.8354223***	0.9978734	1.206463***
	(0.0132423)	(0.0167281)	(0.0256467)	(0.0120901)
Crisis*Primary	1.047651*	1.026667	1.322553***	1.299416***
	(0.0276652)	(0.0588675)	(0.0823926)	(0.0169568)
Crisis*Second Home	0.8720258***	1.167268*	1.181401	0.9463915**
	(0.035357)	(0.1094004)	(0.1224413)	(0.023773)
Crisis*Mortgage Insurance	0.995971	0.898037***	1.397985***	0.9554924***
	(0.0156363)	(0.0191148)	(0.0408547)	(0.0105589)
Crisis*Loan Age	1.008991***	0.9975192***	0.9914432***	1.00732***
	(0.0002795)	(0.0003663)	(0.9914432)	(0.0002122)
Crisis*Time since Default	0.9839944***	1.009458***	0.9970735***	1.006386***
	(0.0004047)	(0.0006454)	(0.0008194)	(0.0003648)
Crisis*Balance	0.8287151***	1.02277*	0.776827***	1.073418***
	(0.0082589)	(0.0139543)	(0.0143538)	(0.0076274)
PostCrisis*Credit Score	0.9979142***	1.001231***	1.00201***	1.001096***
	(0.0001227)	(0.0001406)	(0.000465)	(0.0001158)
PostCrisis*Debt-to-Income	1.00375***	0.9987286**	0.9885643***	1.000744
	(0.000552)	(0.000679)	(0.0023001)	(0.0005175)
PostCrisis*Loan-to-Value	1.013045***	1.002297***	0.9926131***	0.9929254***
	(0.000518)	(0.0008326)	(0.0019498)	(0.0005755)
PostCrisis*Joint	0.8547463***	0.8833497***	1.022381	1.012898
	(0.0121353)	(0.0146673)	(0.0592302)	(0.0138949)
PostCrisis*Judicial	0.9699679**	1.162247***	1.081387	1.339612***
	(0.0138876)	(0.0197017)	(0.0609493)	(0.0172612)
PostCrisis*Non Recourse	1.026596	1.000141	0.9280678	1.136726***
	(0.0180153)	(0.0219055)	(0.0700453)	(0.0190679)
PostCrisis*Not Single-Family	1.059284***	1.219916***	0.796807***	0.795176***
	(0.019325)	(0.0282074)	(0.0532622)	(0.0129137)

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Table 5.8

Variable	Cure	Mod. Success	Mod. Failed	Liquidation
PostCrisis*TPO	0.997206	0.8542656***	0.839824**	1.198944***
	(0.0186669)	(0.017439)	(0.0759242)	(0.0225268)
PostCrisis*Non-Cashout Refi	0.9519342***	0.9189425***	0.9920336	0.8810247***
	(0.0166832)	(0.0190955)	(0.0826131)	(0.0153319)
PostCrisis*Purchase	0.9169174***	0.9373134***	1.125429	0.9620849***
	(0.017438)	(0.0213458)	(0.0925379)	(0.0177853)
PostCrisis*Primary	0.7634985***	0.5940141***	0.6050288***	1.165172**
	(0.0234577)	(0.0352494)	(0.0705954)	(0.0255557)
PostCrisis*Second Home	0.67404***	1.030323	1.007776	0.9022701***
	(0.0336088)	(0.100855)	(0.2164931)	(0.0377654)
PostCrisis*Mortgage Insurance	0.8770353***	0.9453687**	1.165735**	1.179869***
	(0.0174)	(0.0220617)	(0.0817396)	(0.0203252)
PostCrisis*Loan Age	1.003561***	0.9919536***	0.9971714***	1.006181***
	(0.0002907)	(0.0003732)	(0.0008253)	(0.0002572)
PostCrisis*Time since Default	0.983216***	1.013469***	0.9956214***	1.004174***
	(0.0004597)	(0.0006727)	(0.0014203)	(0.0004371)
PostCrisis*Balance	1.13926***	0.8028575***	0.6378417***	0.886807***
	(0.0137818)	(0.011995)	(0.030917)	(0.0104246)
IR Spread	0.8329211***	0.926404***	1.05458***	1.166108***
	(0.0023849)	(0.0021798)	(0.0050298)	(0.0020882)
Ump_{12}^{lag2Yr}	1.00488***	0.9781529***	1.023577***	1.007355***
	(0.0016785)	(0.0012117)	(0.0026392)	(0.0008891)
During-HAMP	1.490014***	0.0012117***	0.5589883***	1.007433
	(0.0169977)	(0.0112292)	(0.0074056)	(0.0057415)
Post-HAMP	1.415005***	1.874568***	0.2208739***	0.6876336***
	(0.0271449)	(0.0284187)	(0.0143767)	(0.0098368)
Region FE	Yes			
Log-Likelihood	-5970679.5			
Pseudo R2	0.0312			
N.Observations	23,293,151			
N.Mortgages	1,453,556			

Chapter 6

Conclusions and Future Work

Residential mortgages constitute a pivotal segment within the banking and lending industry, both regarding volumes and total exposure. Due to the significant impact of this asset class on borrowers, it is also of considerable importance to policymakers and governments. The Global Financial Crisis exemplifies this importance, evidenced by the resultant financial and socio-economic disruptions it caused. However, certain research areas related to this topic have diminished over time as the crisis's effects have subsided. This research contributes to the field by enhancing the literature on residential mortgages from diverse perspectives.

This final section encapsulates the work conducted in this Thesis. Initially, it delineates the primary contributions from each empirical chapter, emphasising how our research has expanded academic and industry understanding of residential mortgage risk management. Subsequently, it demonstrates the practical implications of our discoveries on both industry and academia. Lastly, it concludes by outlining the inherent limitations in the analysis conducted, proposing future research areas to augment this strand of academic literature.

6.1 Key Findings

The main findings of this Thesis can be summarised as follows.

The first empirical chapter of this Thesis scrutinises the role of correlation within residential mortgage portfolios. Correlation measures the degree of interconnection between borrowers in reaction to a single risk factor that influences financial and economic environments, subsequently affecting mortgages and borrowers behaviour. This parameter carries supreme significance for both regulatory and economic capital allocation as it guides their final estimations. The regulatory correlation parameter for retail mortgage portfolios is typically assumed to be a flat value, an assumption often adopted for economic capital calculations too. Nevertheless, following the work of Cowan and Cowan (2004), researchers have started to challenge the flat nature. Our research offers substantial contributions to the existing literature in several respects. Firstly, we utilise the Global Financial Crisis as a benchmark and employ a unique methodology to illustrate how loan and borrower characteristics significantly influence correlation in mortgage portfolios. We examine a 'prime' portfolio (contrasting with exclusive focus on subprime lending as in Cowan and Cowan (2004)) to prove that loan balance and debt-to-income ratios influence correlation patterns more considerably than other loan and borrower characteristics. The importance of balance is notable as it establishes a parallel with current regulatory correlation requirements for SMEs and Corporate exposures. Based on the data utilised, we also find that the 15% value set by regulatory bodies is adequately conservative for the mortgage segment under inspection. Another significant contribution of our research lies in the scarcely explored link between flat correlation and regulatory capital arbitrage. We reveal that lending institutions, which have to comply with international regulatory standards due to their GSIB classification, tend to price correlation negatively, unlike those not under such obligation. This suggests a potentially disruptive mechanism where these lenders could attract riskier mortgages that increase portfolio correlation, yet enhance profitability despite regulatory compliance.

The second empirical chapter investigates the determinants of post-modification resolutions, subsequent to the cessation of the major US governmental program advocating mortgage renegotiations, i.e. the Home Affordable Modification Program (HAMP). Mortgage modifications, which consist of a shift in contractual terms to secure a more manageable loan, were relatively rare prior to the Global Financial Crisis. However, the crisis-induced rise in defaults necessitated an alternative to foreclosure, leading to the US Government's implementation of HAMP to encourage modifications to mortgage contractual terms. A substantial body of literature has probed the effects of HAMP scheme on post-modification outcomes, focusing on how the program influenced borrower post-modification behaviour. Yet, there has been no research to ascertain if the same conclusions are valid over a longer term, particularly after the termination of the governmental program. Our paper expands the existing literature in this direction, investigating the driving forces behind post-modification outcomes following the removal of HAMP. Our key findings reveal that modifications remain an efficacious tool to avert mortgage foreclosures. Payment reductions continue to yield a positive effect, whether achieved by extending the loan term or reducing the contractual interest rates. However, the impact is not uniform across policy periods, as interest rate reduction emerges as a more powerful measure once HAMP has been discontinued and modifications have been fully assimilated into the mortgage system. Another significant finding is the efficacy of timely modifications in helping borrowers maintain a current status post-modification, unaffected by the time frame of analysis. Lastly, we examine modifications during periods when temporary payment suspensions were also offered, to differentiate between strategic and non-strategic borrowers. Our findings suggest that non-strategic borrowers (i.e., those genuinely requiring modification) exhibit superior post-modification behaviour.

The final empirical chapter examines another vital aspect of mortgage risk management: post-default resolutions. When a borrower defaults by missing three or more payments, several scenarios may arise as potential exit strategies, including cure, modification, or liquidation. These exit statuses are crucial for banks and mortgage lenders as they impact the capital and provisions' loss side. The chapter delves into the determining post-default factors, namely the characteristics of the loan, borrower, and state, that can uniquely influence the exit status from default. Despite prior academic studies into this subject, our research builds upon the existing body of work by using a sample scarcely explored in this field and differentiating across the most pertinent disruptions in the mortgage market. The key findings of this concluding chapter can be summarised as follows. Firstly, we affirm the importance of some post-default determinants previously tested in literature, even within GSE portfolios, thereby generalising results that were limited to sub-prime portfolios only. Secondly, the study identifies new determinants not considered in previous studies, discovering that they are significant post-default predictors. For instance, holding a joint mortgage significantly aids in positive default status resolution. We also highlight variations in state-level laws, a topic not previously covered, and discover that judicial laws slow down post-default exits across all potential statuses. Lastly, the most significant finding pertains to the influence of mortgage market and policy cycles on post-default resolutions. Our research underscores that the implementation of specific policies, such as HAMP, obscures the typical influence of post-default determinants across all potential exit statuses. In some instances, the impact is temporarily disrupted, while in others, the change becomes permanent.

6.2 Implications for the Industry

Given the empirical approach undertaken for the development of this work, we believe that both our research questions and our findings can have several implications for policymakers and mortgage industry. We now illustrate each of these across the three studies undertaken.

The first implication pertains the regulatory usage of a flat value, as we have shown that it might not well capture the responsiveness of mortgage segments to economic shocks. A deeper understanding of correlation variability, especially for institutions holding large portfolios of mortgages, is therefore essential. In fact, this work could motivate larger financial institutions to explore the reaction of their mortgage portfolio using the Global Financial Crisis (or any other downturn period) as a benchmark for their internal computation of correlation for economic capital allocation. In addition, such analysis might help discovering whether portfolio correlation is driven by additional characteristics that we have not considered, or if it is influenced by the type of business run by the institution or by the jurisdiction under consideration. A further expansion of this analysis can involve additional asset classes that currently lie on a flat correlation assumption (like credit cards). In general, expanding the understanding of portfolio correlation can be very beneficial for risk managers. The second implication that the first empirical chapter offers is related to policymaking. Following the analysis that pertains to correlation and mortgage pricing, we highlight that regulatory frameworks and policy restrictions implicitly drive lenders behaviour. Specifically, the analysis shows that a flat value of correlation, being sufficiently conservative, determines a form of regulatory capital arbitrage, by negatively influencing mortgage pricing only for those institutions that are required to be compliant to regulatory standards. This is an important point both for policymakers and financial institutions. Concerning the first, second-layer controls should be put in place across different fronts. In first instance, a constant monitoring of the correlation parameter, alongside sensitivity checks across alternative data and/or assumptions should be put in place. It must be reminded, in fact, that the 15% correlation parameter has never been changed since the introduction of Basel II accords. Regulatory bodies (or central national banks) should also assess if the 15% assumption is not promoting pockets of risky lending, by implementing second-level controls for banks' risk appetite in relation to portfolio correlation. This same exercise should be also performed internally, to make sure that shareholders and stakeholders are well informed of the implicit risks that the credit institution is undertaking.

The second and third empirical chapters yield significant implications for both policymakers and industry practitioners. Firstly, the second empirical chapter demonstrates that modifications remain a valuable tool for distressed borrowers, even after the cessation of government schemes, and highlights its effective absorption within the mortgage market. This finding has both policy and industry implications, as it underscores the utility of renegotiations as a viable alternative to foreclosure, even beyond crisis periods. Lenders who have become reluctant to grant renegotiations should reconsider this option more proactively. Additionally, the industry can benefit from increased awareness of modification types that prove effective in a post-policy environment, which may vary over time and are influenced by the period under examination. Furthermore, from a risk-management perspective, lenders should differentiate between borrowers who strategically seek modifications from those who do not, which is crucial for a correct and precise risk monitoring. This differentiation can help identify consumers who can genuinely benefit from renegotiations and those likely to face liquidation. Moreover, it is essential to monitor such behaviour as it may evolve over time and can be influenced by market fluctuations.

With regard to implications, the findings and analyses presented in the third empirical chapter primarily contribute to the domain of risk management. However, they also underscore policy contributions within the mortgage market. Initially, the chapter emphasises the necessity to accurately distinguish between various exit statuses from default, be it through cure, modification, or liquidation. Enhancing modelling capabilities in this regard would facilitate risk managers in comprehending the dynamics of mortgages comprehensively, and identifying those determinants leading to each potential outcome. This not only advocates for more accurate provision or capital planning, but also promotes improved post-default implementation strategies. This latter point holds relevance for both lenders, managing their mortgage cash-flows directly, and servicers, in instances where such practice is outsourced. Simultaneously, an improved modelling framework enables the overcoming of simplistic assumptions typically adopted by regulatory frameworks, largely confined to models of default probability and severity. Second, the chapter provides a crucial perspective on how market disruptions and the implementation of governmental policies shape and influence the primary post-default drivers. In this context, the paper emphasises that specific temporal periods can modify borrowers and mortgage's sensitivity to certain risk determinants. Thus, it is vital to judiciously select the sampling period for any study that may encompass the activation of policy schemes or governmental interventions, as these periods may alter borrower behaviour and subsequently drive model estimations. This aspect is also critical for policymakers, who should remain cognisant of the changes they introduce into the market and their impact on borrower repayment patterns.

6.3 Limitations and Areas of Future Research

As our research is empirically based, we acknowledge potential limitations stemming from both the data and the assumptions employed. Therefore, this section outlines weaknesses in the analyses and identifies opportunities for future research to address these limitations. Additionally, considering the time constraints inherent in any study, we recognise that certain analyses might have benefited from more extensive exploration. Consequently, we also recommend areas for future research that could augment our findings.

Regarding the initial empirical chapter, it is imperative to highlight two significant areas of weakness: the first pertains to the data utilised, and the second concerns the methodology applied. Firstly, it must be acknowledged that the sample derived from Freddie Mac, utilised in this study, encompasses only conforming single-family and fixed-rate mortgages. Generally, conformity rules are met by loans categorised as prime or near-prime, subject to mitigating factors. Consequently, our analysis does not include adjustable-rate, multi-family, and jumbo loans, as well as portfolios exclusively composed of sub-prime or near-prime loans. These loan types are under-represented in our sample, yet they are more likely to be found in a typical commercial bank's mortgage portfolio due to the rarity of their sale to government-sponsored entities or private securitisation agencies. Nonetheless, the predominance of conventional loans in the mortgage market serves as a mitigating factor to such limitation. Conventional loans, along with their associated borrowers, accurately represent the archetypal mortgage customer in the U.S., thereby likely featuring prominently in a standard commercial bank's mortgage portfolio. It would be beneficial for future research to extend the analysis to include the aforementioned mortgage segments that we have not considered, as they may display variances in sensitivity to identical risk factors. This recommendation also applies to other potential areas of expansion not explored in this study, such as regional segmentation or the utilisation of data from different legal jurisdictions or countries, which could reveal whether the factors considered influence correlations similarly or if alternative factors dominate. Furthermore, examining additional periods of crisis, such as the COVID-19 pandemic, could yield further insights into this field of research.

The last observation concerning the dataset pertains to the employment of time-invariant variables, such as Credit Score or Debt-to-Income Ratio, which are assessed solely at the point of origination. This limitation stems from the nature of agency data, as Government-Sponsored Enterprises (GSEs) primarily focus on acquiring regular updates regarding cash flows, deeming the borrower's initial characteristics sufficient. However, periodic updates on these metrics would have enhanced our study, as recent data on the borrower's risk profile or affordability could more accurately reflect correlation dynamics. Investigating these elements in future research could enrich our findings and bring a valuable perspective to the academic discourse. The second limitation, already briefly discussed in the main text, concerns the application of copula models, which were employed to ascertain correlations (Egami and Kevkhishvili (2017)). Despite the critique, this approach has been extensively utilised in this field; thus, we remain confident of our methodology. Future studies could explore alternative methodologies to verify and broaden the scope of our framework.

In relation to the empirical analyses presented in the second and third chapters, the primary limitation stems from the dataset utilised. While Freddie Mac data encompasses a significant portion of mortgages issued in the US, the eligibility criteria inherently restrict the types of customers and mortgages examined. Consequently, the insights pertaining to both post-modification and post-default outcomes during the post-HAMP era may not fully encapsulate the spectrum of mortgages found on bank balance sheets or those sold to the secondary private mortgage market. Future studies could, therefore, explore post-modification and post-default outcomes across a broader range of mortgage types. Moreover, the reliance on Freddie Mac data precludes the examination of principal reduction as a potential explanatory factor for the observed outcomes. Employing an alternative dataset would enrich the analysis by illustrating the effects of principal reduction on post-renegotiation resolutions in the aftermath of HAMP's cessation and the assimilation of modifications within the market. Additionally, this research is confined to fixed-rate mortgages, thereby omitting the analysis of how recent interest rate increases affect the behaviour of adjustable-rate mortgages with respect to both phenomena under investigation. This limitation presents a compelling dimension for subsequent research.

A second limitation of both studies concerns the time-frame utilised for analysis during the post-HAMP (or crisis) periods. Despite our efforts to encompass the broadest possible time-frame, the timing of our study restricts our observation of the post-HAMP period to a maximum of six years. Moreover, the more recent materialisation of both modifications and defaults in the post-crisis era results in a shorter post-event observation window. This limitation curtails our ability to monitor mortgage behaviour over an extended horizon, leaving the examination of our findings' validity over a more substantial observation window as a future research avenue, potentially through replication of the analysis in a few years. Additionally, the second and third empirical chapters are limited by the types and numbers of resolutions examined. For post-modifications, we considered Delinquency, Liquidation, and Prepayment; for post-default, we analysed Cure, Modification, and Liquidation. Our selection was dictated by data availability. However, utilising alternative datasets could broaden the scope of outcomes under review, offering a more comprehensive analysis spectrum. For instance, Phillips and VanderHoff (2004) also incorporates Prepayment in the post-default analysis, a consideration we omitted due to data constraints.

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